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MASTER'S THESIS

Income Inequality and Economic Growth: A Meta-Analysis

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Declaration of Authorship

The author hereby declares that she compiled this thesis independently, using only the listed resources and literature.

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Abstract

The impact of inequality on economic growth has become a topic of broad and current interest. Multiple researches investigated the issue but the disparity of opinions and empirical results is huge. The present thesis revises the primary literature through a meta-analytical approach applying Bayesian Model Averaging (BMA) estimation technique. We examine 562 estimates collected from 58 studies published between 1991 and 2015. I find the evidence of the publication bias presence in the literature. The authors of primary studies tend to report preferentially negative and significant estimates. The BMA results suggest that the effect of inequality on growth is not straightforward and is likely not linear. A single pattern for inequality/growth relationship is not feasible since the results vary across used income inequality measures, estimation methods and data structure and quality.

JEL Classification	D31, O10, C11, C82
Keywords	meta-analysis, inequality, economic growth, Bayesian model averaging, publication bias

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Abstrakt

Vliv nerovnosti na hospodářský růst se nedávno stal tématem širokého zájmu. Tomuto tématu se v poslední době věnovala řada akademických publikací, v řadě případů však autoři docházeli k rozdílným výsledkům. Tato diplomová práce dostupnou literaturu reviduje a reinterpretuje za použití meta-analytických metod a Bayesiánského modelu průměrování (BMA). Zkoumáme 562 odhadů sesbiraných z 58 studií zveřejněných mezi lety 1991 a 2015. V literatuře jsme identifikovali důkazy přítomnosti publikační selektivity. Autoři primárních studií mají tendenci vykazovat přednostně negativní a významné odhady. Výsledky BMA naznačují, že účinek nerovnosti na ekonomický růst pravděpodobně není lineární. Zdá se, že mezi nerovností a ekonomickým růstem neexistuje jednoznačný vztah, protože výsledky se liší v závislosti na použitých mírách měření nerovnosti příjmů, metodách odhadů a struktuře a kvalitě dat.

Klasifikace JEL	D31, O10, C11, C82
Klíčová slova	meta-analýza, nerovnost, ekonomický růst, Bayesian model averaging, publikační selektivita

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Acronyms

BMA Bayesian Model Averaging

FAT Funnel Asymmetry Test

FE Fixed Effects

FGLS Feasible Generalized Least Squares

GDP Gross Domestic Product

GMM Generalized Method of Moments

IV Instrumental Variable

LDC Least Developed Countries

LIS Luxembourg Income Study

MCMC Markov Chain Monte-Carlo

ME Mixed Effects

MLE Maximum Likelihood Estimation

MRA Meta-regression Analysis

OLS Ordinary Least Squares

OECD Organisation for Economic Co-operation and Development

PET Precision Effect Test

PIP Posterior Inclusion Probability

PMP Posterior Model Probability

PPI Price Level for Investment

RE Random Effects

SE Standard Error

SMLT Simultaneous Systems

WIID World Institute for Development Economics Research

WLS Weighted Least Squares

2SLS Two-stage Least Squares

Master Thesis Proposal

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Proposed topic	Income Inequality and Economic Growth: A Meta-Analysis

Motivation The issue of wealth and income inequality is the great moral issue of our time, it is the great economic issue of our time, and it is the great political issue of our time. (Bernie Sanders, 2016) It is true that income disparities have become more and more pronounced for the past half century not only in the US but throughout the world. Economists are thus more and more focusing on the relationship between inequality and economic growth. The topic of income distribution and its relationship with growth was initially raised by Kuznets in his famous article (1955). However, though explaining the evolvement of income distribution through different stages of economic development, it doesn't directly state whether inequality is detrimental to growth. Several theoretical and empirical studies tried to answer this question but the disparity of opinions and empirical results is huge and the debate still seems to be open.

Meta-analysis is a practical way of dealing with contradictive results of empirical literature. It is based on the collecting of numerous various estimates and their quantitative summarization. Applications of recent meta-analyses in economics field are numerous, including studies on FDI spillovers (Irov & Havrnek, 2013), fiscal and monetary policy issues (Gechert, 2013; Havrnek & Rusnak, 2013) and others.

One meta-analysis on the topic of inequality and growth has already been published by Dominicis, Florax, and de Groot (2008). The main conclusion of the paper is following: there doesn't exist a straightforward relationship between these two variables - the estimated correlation is largely dependent on the used estimation methods, data quality, sample coverage and growth period length (short run vs long run).

There is an evident limitation to this meta-analysis: it was published almost 10 years ago, which means that recent articles are not included in it. The main goal of this paper is to widen the existing dataset and employ better methodology (see Methodology part lower) in order to shed new light on the topic. I will also try to search for the dependencies of the resulting coefficients on the papers' dates of publication.

Hypotheses

1. Hypothesis 1: Literature resources focusing on the relationship between income inequality and growth are subject to reporting bias.
2. Hypothesis 2: The degree to which inequality influences growth is exaggerated due to present reporting bias.
3. Hypothesis 3: The average resulting coefficient is higher and negative in the papers published after the global financial crisis of 2007-2008.

Methodology The existing dataset of Dominicis, Florax, and de Groot (2008) serves as the foundation for the research conducted in this paper. The dataset will be widened by the studies published after the year 2008, which I will thoroughly choose from academic electronic sources of literature available at Google Scholar, EBSCO Host, ResearchGate etc. I will select the studies according to the following criteria: the presence of both the coefficient and the standard errors in the research and the use of Gini coefficient as a primary measure of inequality.

The first step of this meta-analysis will be discovering the presence of the publication bias, using the funnel plot and tests for detecting asymmetry of the funnel plot. In the absence of publication bias studies with the results of high precision will be plotted near the average while studies with the low precision results will be spread on the sides of the average in the form of a funnel-shaped distribution. Publication bias, however, assumes deviation from this shape. In simple words, authors are likely to publish the results, which are statistically significant, while null results are tucked away. Since the regression containing the bias is likely to be heteroscedastic, I will use weighted least squares, where the inversed standard errors will be used as weights, to control for heteroscedasticity.

Due to unobserved between-study heterogeneity (arising because the estimate, combined out of effects in individual studies, can't be a description of the set of studies, since studies use different data) I will use the so-called mixed-effects multilevel model for estimation. I will also apply Bayesian Model Averaging (BMA) technique in order to deal with the uncertainty in the model arising due to the probability of excluding relevant variables, when selecting the model's specification. To check the robustness of the results I will use the frequentist check of the BMA exercise.

Expected Contribution In this paper I will conduct a quantitative survey of articles on the economic growth dependence on the income inequality. The main purpose of this paper is to improve the dataset of Dominicis, Florax, and de Groot (2008) with the extension of the literature and applying wider methodology. Furthermore, I will try to search for a trend in the resulting coefficients dependence on the papers' dates of publication in order to prove my hypothesis that the coefficients were expected to be higher and negative after the global financial crisis of 2007-2008.

Outline

1. Introduction to the topic
2. Theoretical and empirical literature overview
3. Methodology: The description of main estimation techniques and methods
4. Empirical analysis
   (a) Data and model description
   (b) Description of results
5. Concluding remarks: Main findings and conclusions

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Author Supervisor

Chapter 1

Introduction

Increasing inequality in global society both within and between countries is undoubtedly one of the biggest social, economic and political issues of our time. Income disparities, which have become more and more pronounced for the past half century, and their correlation with other economic variables have gained significant attention among economists and policymakers. Particularly interesting is the impact of income inequality on economic growth, which has been a topic of broad and current interest for the past 60 years since the prominent article by Kuznets (1955) was published. Kuznets succeeded in explaining the evolvement of income distribution through different stages of economic development highlighting the non-linear relationship between growth and inequality. Yet, his findings opened a new debate on the opposite causality of two variables (inequality impact on growth) - a debate which is still open.

A huge number of both theoretical and empirical studies have emerged during the past decades attempting to determine the direction of correlation between income distribution and economic environment. The disparity of opinions and empirical results is striking. Theoretical studies claiming for a positive impact of inequality on growth relied on the idea of higher accumulation of physical capital and propensity to save by wealthier agents, which leads to the increase of aggregate savings, investment and, as a result, economic growth. Meanwhile, the opponents focused on the transmission channels through which inequality affects growth (fiscal, market, political and social distortions) and justified the negative correlation of two variables.

Empirical evidence is not less controversial. Earlier studies mostly relied on cross-sectional data and tended to produce the results supporting negative correlation of income inequality and growth. Yet, with the implementation of more sophisticated econometric techniques and the use of larger panel data samples later authors found evidence on a positive relationship of the two variables. By contrast, recently emerging studies call the linear inequality on growth impact into question and suggest non-linear estimation methods might be more appropriate when examining the variables' relationship.

A meta-analysis is a useful way of how to deal with controversial empirical results. One meta-analysis on the topic of income inequality and economic growth has already been published by De Dominicis *et al.* (2008). Mainly, the authors infer that the relationship between income inequality and economic growth is not unequivocal. The magnitude of the estimated effect coefficient of income inequality on growth is largely dependent on the methodology and quality of the data sample. The principal conclusions of the meta-analysis by De Dominicis *et al.* (2008) can be summarized as follows:

- the inequality on growth effect is more negative and significant in less developed countries and when the higher length of the growth period is considered
- the studies employing fixed effects estimation method report higher effect size coefficients
- when regional dummies and other measures of inequality (human capital, land-ownership inequality) are used as regressors in the primary studies, the effect of income inequality on growth tends to be weaker
- the income's definition and the data on income distribution quality (Gini quality) are largely impacting the results, particularly:
  - if the income measure is based on expenditures rather than income or if the poor-quality data on income is used, the resulting coefficient is highly significant, negative and large in magnitude
- it is inappropriate to speak of a simple positive or negative relationship between income inequality and economic growth since the differences in estimation methods, data quality and sample structure largely influence the estimated effect size coefficient.

Though providing with such convincing conclusions, there are two evident limits to the De Dominicis *et al.* (2008) paper. Firstly, it was published 10 years ago and therefore the most recent articles are not included into the meta-dataset. Secondly, there is room for the methodology improvement. Some modern estimation techniques (see Chapter 3: Methodology) that were not yet applied in the field of income distribution, could shed new light on the topic.

The main objective of this thesis is to widen the existing De Dominicis *et al.* (2008) dataset and employ more sophisticated methodology. Based on 562 estimates collected from 58 primary literature sources (both journals and working papers), the following thesis examines potential publication bias and heterogeneity of the reported results with the help of econometric meta-analytical tools: graphical illustrations, regression tests and heterogeneity detection techniques. Specifically, Bayesian Model Averaging approach is employed in order to explain the determinants of heterogeneity. These modern tools help to resolve the uncertainty in the model arising due to the probability of excluding relevant variables, when selecting the model's specification.

The main hypotheses of the thesis are as follows: (i) primary studies which constitute the meta-dataset are subject to reporting bias, (ii) the degree to which inequality influences growth is exaggerated due to present reporting bias, (iii) the average resulting coefficient is higher and negative in the papers published after the global financial crisis of 2007-2008.

One of the goals of the following thesis is to search for the dependencies of the resulting inequality on GDP growth effect size coefficients on the primary papers' publication dates. The third hypothesis arises from the intuition that after-crisis pessimistic sentiments could have likely induced the authors to be biased in favor of negative estimate results. Interestingly, the crisis of 2008 coincided with the publication year of De Dominicis *et al.* (2008) paper. Therefore, the subsample of "after crisis" studies is at the same time the subsample of new studies published after De Dominicis *et al.* (2008) paper issue and thus not included into their dataset.

The thesis is composed of several chapters. Chapter 2 provides with the literature review on the topic. The main theoretical foundations and empirical literature results from the studies of the past 2 decades are described and compared. Chapter 3 is devoted to the methodology implemented further in the thesis. Specifically, the meta-analytical techniques, such as publication bias graphical detection, meta-regression tests and Bayesian Model Averaging concept are delineated. The chapter also addresses the criticism of the meta-analytical approach. Chapters 2 and 3 thus serve as a solid theoretical background for the empirical research conducted further in Chapter 4. Chapter 4 presents the research observations by means of graphical tools, econometric tests and regression analysis. The last part of the thesis summarizes the core findings and results and provides with suggestions for further research on the topic. Appendix A contains a list of primary studies included in the meta sample. Appendix B includes all auxiliary results from the BMA regression. Appendix C presents a correlation matrix of explanatory variables.

Chapter 2

Literature review

The topic of income inequality and its relationship with economic output was initially raised by Kuznets (1955). According to the author the relation between inequality and per capita income follows an inverted "U" shape.

With the development of economy (from a rural to an industrial stage) the influx of labour and resources to the urban areas escalates. Per capita income and investment opportunities increase only for a limited group of relatively wealthy people who move. Inequality deepens.

Subsequently, with the gradual mechanization of agriculture more and more rural workers enter the industrial sector. Simultaneously the wages in the agricultural sector rise driven by the reduction in rural labour force. Policy makers are thus forced to redistribute income more fairly, which leads to a downtrend in inequality.

Though explaining the evolvement of income distribution through stages of economic development, Kuznets' theory doesn't directly state whether inequality is detrimental to growth. Starting to emerge mainly in the 90s, several theoretical and empirical studies further attempted to answer this question.

2.1 Theoretical foundations

Before digging further into the topic of inequality/growth relationship it is worth mentioning that the definition of inequality has notably changed during the past two centuries. Inequality measures in modern affluent societies considerably exaggerate real inequality. The differences in income and accumulated wealth among individuals nowadays do not always indicate substantial inequality in opportunities and life quality. Looking backwards at earlier societies where the existence of middle-class was far from being established, it is clear that the gap between those who could afford to lead a prosperous life and those merely surviving was astonishing. The studies considered in this research were not published earlier than three decades ago, which suggests their authors must have had a comparable understanding of what constitutes inequality in modern societies.

A number of earlier theoretical works were published in the 90s. The literature authors mostly advocate a positive correlation between income and economic growth. Aghion *et al.* (1999) rely on 3 arguments to prove the growth-enhancing effect of inequality. Firstly, rich are more inclined to accumulate savings than the poor. Therefore, if the proportion of saved national income is linked to the GDP growth rate, unequal economies should have a more rapid growth than those with the even income distribution. Secondly, investment projects require sufficient sunk costs, which calls for wealth concentration within the hands of group of individuals. Inequality thus allows creating new investment activities, which in turn enhances growth. Finally, if wealth is equally distributed, it discourages the workers to exert effort, which leads to economic inefficiency and lower output.

A relatively recent study by Galor & Moav (2004) asserts positive impact of inequality on growth in the initial stage of country's industrialization, when physical capital accumulation is the key driver of growth. According to the authors, in the early stage the rate of return to physical capital (which is in short supply) is higher than to human capital. Poor agents consume their entire wages, don't possess any savings and thus don't invest. Agents with high income, on the other hand, accumulate physical capital. This inequality increases the wealth of those with a higher propensity to save, boosting aggregate savings and growth.

Other studies using theoretical models advocate a detrimental effect of wealth inequality on growth. They, however, differ in the perception of what is a key determining factor of the variables' adverse relationship.

Some rely on the assumption, that inequality negatively affects growth through **fiscal distortions**. Poor agents tend to support governments advocating higher taxes. (Poor pay a smaller share of taxes and their benefit from elevated taxes is disproportionately higher.) The unequal income distribution in the economy (where the number of poor agents is high) will, therefore, through prevalence of high taxes, decrease growth by deterring investment. Persson & Tabellini (1994), Alesina & Rodrik (1994) and Bertola (1991) all rely on the models, where the negative correlation between inequality and growth is induced by the government fiscal policies.

Another view is represented by the studies (Banerjee & Newman (1991), Galor & Zeira (1993), Chiu (1998)), which consider **the presence of market imperfections** as a key driver of inequality/growth adverse relationship. Poor agents face borrowing constraints because of imperfect information and thus can't easily accumulate capital. Therefore, markets with unequal income distribution lack investment in human and physical capital, which negatively affects economic growth.

Galor & Moav (2004), though finding evidence for the positive inequality/growth relationship in the early stage of economic development due to physical capital accumulation, stress the crucial role of human capital (normalized by education) in the later stage. Since poor agents are constrained by their initial level of wealth, their investment in human capital is limited. Equality mitigates the burden of credit constraints, which poor agents carry, and allows for higher aggregate human capital investment, stimulating economic growth.

Perotti (1996) and De La Croix & Doepke (2003) view human capital's intermediary role in inequality/growth relationship through a trade-off between the quantity and "quality" of children, that agents face. The cost of education is represented by the income sacrificed for not working. An inegalitarian society is the one, where less people can invest in human capital through education. Authors find that fertility is lower for more educated people (who possess more human capital). Agents with less ability to invest in human capital and lower education thus make up a larger share of overall population in unequal societies, and the growth is diminishing.

Apart from fiscal distortions and capital accumulation within imperfect markets, **political and social instability** in economies with unequal income distribution is also considered a channel through which inequality hampers growth. According to Alesina & Perotti (1996), inegalitarian societies are prone to political tensions and higher rates of crime and violence. It triggers uncertainty and has a negative impact on the level of investment, which in turn impedes economic growth. Bourguignon (2000) supports the idea that poor agents engage in criminal activity and that even temporary rise in inequality results in elevated crime rate. Keefer & Knack (2002), Collier & Hoeffler (2004) and Temple (1999) see inequality as a phenomenon, which increases the cost of social interaction and economic exchange. The resulting social segregation leads to lower growth and even poverty traps in case of some countries.

2.2 Empirical literature

Empirical literature on the topic also falls into two camps. While some studies claim for positive correlation between two variables, others provide with evidence of detrimental impact of income inequality on growth. The differences in results may be due to multiple factors: data quality and format, chosen estimation methods, set of control variables, time period and sample selection.

Speaking about data quality and format, the majority of the studies use Gini index [1] as an inequality measure within the research. Other measures of inequality, such as Theil index or share in income of a certain quantile are used as well. This meta-analysis focuses on studies considering Gini coefficient only.

There are several sources for data on inequality (with the Gini index as a measure) used in the empirical studies: Deininger & Squire (1996), Luxembourg Income Study (lis) dataset, World Institute for Development Economics Research (wiid) dataset and Jain dataset (1975). More recent studies also rely on data from OECD, WorldBank and Eurostat.

Deininger & Squire (1996) dataset (with around 680 observations for 108 countries) claims to be the best in terms of data reliability since it provides high-quality data on income distributions. The data meet three criteria to be considered "high-quality", according to Deininger & Squire (1996): estimates are drawn from household surveys, measures of inequality are based on comprehensive coverage of all possible sources of income (not only wages) and expenditures, and inequality measures represent the entire population (not only urban or rural population).

Estimation methods and techniques largely vary within the empirical literature on the topic. While many authors assume simple linear estimation to be applicable, some advocate its inappropriateness and assert a non-linear inequality/growth relationship. Same disparity is observed in the choice of data samples' structure.

Earlier studies mostly relied on cross-sectional structure of the data (Alesina & Rodrik (1994), Clarke (1995), Deininger & Squire (1998), Figini *et al.* (1999), Knell (1999)). All of them apply OLS or simultaneous system estimators and report negative and significant coefficients regardless the differences in the sample sizes, time periods, control variables and inequality measures. According

[1] Gini coefficient (ratio, index) is a statistical measure of distribution derived from the Lorenz curve. The Gini value ranges from 0 (0%) to 1 (100%), where 0 represents perfect equality and 1 represents perfect inequality.

to Persson & Tabellini (1994) and Perotti (1996), however, the results become insignificant once dummy for regions are introduced into the regression.

Studies emerging later started to, one way or another, criticize the approach of their predecessors. Knowles (2005) argues that results might be biased if data on income and expenditure is mixed when measuring inequality. His findings show that inequality has a significant negative effect on growth only when expenditure data is used, while income distribution triggers insignificant results.

Others (Deininger & Olinto (2000) and Castelló & Doménech (2002)) came up with the critique of the use of income inequality as a proxy for wealth inequality in the majority of previous studies. According to these authors, income inequality is an insufficient measure of wealth, and the inclusion of human capital inequality as a proxy is crucial since the distribution of income is primarily determined by the distribution of human capital. The results based on the above critique yield a more significant negative effect on growth, with less measurement errors.

The majority of empirical literature using cross-sectional data relies on a simple linear growth regression in a form:

$$G = \alpha_0 + \alpha_1 I + \sum_{k}^{K} \alpha_k Z_k + u \tag{2.1}$$

where G is an average annual growth rate of real GDP per capita, I is a measure of income inequality (usually measured by Gini coefficient), Z_k is a set of other growth-impacting variables, and u is an error term.

Such a regression is, however, commonly criticized for its inability to treat an endogeneity problem. There exist multiple factors that could be potential important determinants of the economic growth rate. Institutions, environmental conditions, demography, public policies, technological level are just a small fraction of all such factors that usually can not be observed. In case such an unobserved variable gets absorbed by the error term instead of being included as an explanatory variable, there arises the omitted variable bias problem. An explanatory variable located in the Z_k set of variables becomes correlated with the error term.

By the end of the 90s after the Deininger & Squire (1996) dataset was issued, the possible presence of omitted variables in cross-sectional regressions and the resulting need to apply fixed and random effects models to control for unobserved effects induced the researches to rely on the panel data structure when investigating the inequality/growth relationship. Thus, the equation 2.1 got modified into:

$$G = \alpha_0 + \alpha_1 I + \sum_{k}^{K} \alpha_k Z_k + \xi + \omega + u \tag{2.2}$$

where ξ is a time-specific fixed effect, ω explains the country specifics which are assumed to be constant over time and u comprises the error part which varies over time and over countries.

The first studies to use panel data for estimating inequality/growth correlation were Li & Zou (1998), Székely & Hilgert (1999), Forbes (2000) and Deininger & Olinto (2000). The estimates of these studies when using fixed and random effects are positive, implicating a beneficial effect of inequality on growth. In a dynamic panel model, however, the fixed effect is always correlated with the at least one of the explanatory variables. Besides, since most of the variation for income inequality variable is cross-sectional, the results may be deceptive.

Therefore, other authors tried to solve the endogeneity problem by rather using GMM estimation, since it provides with consistent and efficient estimators in case the assumption of no serial correlation in the error term is satisfied. First difference GMM (proposed by Arellano & Bond (1991)) guarantees consistency through taking first differences of the original variables in order to get rid of country-specific effects and uses the lagged values of explanatory variables as instruments to deal with endogeneity.

The results here vary. Banerjee & Duflo (2003) find a positive statistically significant relationship between income inequality and economic growth. De La Croix & Doepke (2003)'s coefficient is significantly negative, though changing sign and becoming insignificant, if the fertility rate variable is included in the regression. Panizza (2002)'s GMM results also yield negative and significant inequality/growth correlation, which though becomes insignificant if time dummies are introduced.

Castelló-Climent *et al.* (2004) criticises the use of Arellano & Bond (1991) GMM estimator since, if the variables are highly persistent, the lagged levels can't be good instruments for differenced variables. Castello therefore uses more robust (in case of growth regressions) system GMM estimator (developed by Arellano & Bover (1995) and Blundell & Bond (1998)). It allows using variables in first differences as instruments in level equations. The estimator thus enables to combine regressions in differences with regression in levels. Castello's results show positive statistically significant inequality/growth relationship.

Some authors explain the discrepancy of findings described above by the inappropriateness of linear estimation methods. Banerjee & Duflo (2003) doubt data consistency and the validity of linear-form results. According to the authors, changes in inequality in any direction lead to lower growth in the following period. Khalifa & El Hag (2010) suggests that the effect of inequality on growth largely depends on the development stage of an economy. He argues that there exists a threshold of income per capita, below which the inequality/growth relationship is significantly negative and above which inequality does not impact economic growth. Castelló-Climent (2010), Chambers & Krause (2010), and Herzer & Vollmer (2012) find supporting evidence that inequality's negative influence on growth is more pronounced in developing economies and is limited (or even positive) in developed economies.

In general, recently emerging studies question a simple one-direction inequality/growth relationship and arrive to conclusions, that inequality may be detrimental to growth in some cases and, on the contrary, beneficial in other. Fawaz *et al.* (2014), for example, find a positive correlation between inequality and growth in high-income countries, which is in great contrast with negative coefficients for low-income states. Halter *et al.* (2014) obtain positive coefficients when taking into account a short-term horizon but strongly negative coefficients, when the long term is considered. This is explained by the fact that growth-promoting effects of inequality are mostly of economic nature (capital market imperfections, convex saving functions) and tend to materialize quickly. Effects of inequality of a political nature are, on the other hand, more of a growth-hindering character and need more time to come into being. Voitchovsky (2005) concludes that positive and negative effects of inequality on growth are linked to differences in inequality in different parts of the income distribution. An upper end of the income distribution is associated with the positive effect on growth, while a down end with the negative one.

Chapter 3

Meta-analysis methodology

For the past several decades economists have started to more and more focus on the relationship between inequality and economic growth. As the literature review section proves, though, the disparity of opinions is huge and the empirical results largely vary.

Meta-regression analysis (MRA) is a practical way of dealing with contradictive results of empirical literature. "Meta-analysis is the analysis of empirical analyses that attempts to integrate and explain the literature about some important parameter". (Stanley & Jarrell 1989) It is based on collecting of numerous various estimates from previous regression analyses and their quantitative summarization. MRA offers a methodology to map the effect of the researchers' choices of data, estimation techniques, and econometric models onto research literature. (Stanley & Jarrell 1989)

It was already in the beginning of the 20th century, when researches (forced by huge volumes of constantly emerging research) first started to develop quantitative methods to harmonize the results of studies on the same topics and explain their differences. British statistician Karl Pearson was the first to combine observations from various clinical studies comparing the data on soldiers who volunteered for typhoid fever vaccination and those who didn't. (O'rourke 2007) Further contributions to the meta-analysis methodology were made in the 30s by statisticians Robert Fisher and his colleagues working in agricultural and medical research. It was, however, only in 1976 when Gene Glass first used the term meta-analysis referring to it as "the analysis of analyses". (Glass 1976)

Modern applications of meta-analyses in different sciences are numerous, from studies on psychological and health issues to research in economics and other social sciences. Meta-analysis is a powerful tool, which generally has two main goals. The first one is to estimate and explain the excess between-study variation, arising due to differences in data and methods used in primary literature. The second goal is to detect the so-called publication bias in order to find out whether the published results are influenced by authors' subjective intentions.

3.1 Publication bias

Publication bias (also called a file-drawer problem) is a common issue in an empirical research. It arises due to the authors' propensity to publish results, which are statistically significant or more interesting in terms of their impact. The unfavourable (small and insignificant) results are meanwhile tucked away since the authors believe they bring little information about the issue in question. This selective publishing leads to serious bias in the research since true values of estimates in the population are evaluated wrongly.

To be more concrete, there exist 3 major sources of publication bias in empirical economics research according to Card & Krueger (1995):

- The predisposition to publish papers which are consistent with theoretical presumptions and conventional views (leads to over or underestimation of the true effect size)
- The use of the conventionally expected result as a guide in choosing the empirical specifications
- The propensity to treat "statistically significant" results as more favourable (leads to overestimation of the true effect size)

If any of the above is present, the research is unreliable and is no longer a representative sample of the available evidence. On the contrary, in case the estimates are randomly distributed around the true eect there is no publication bias present.

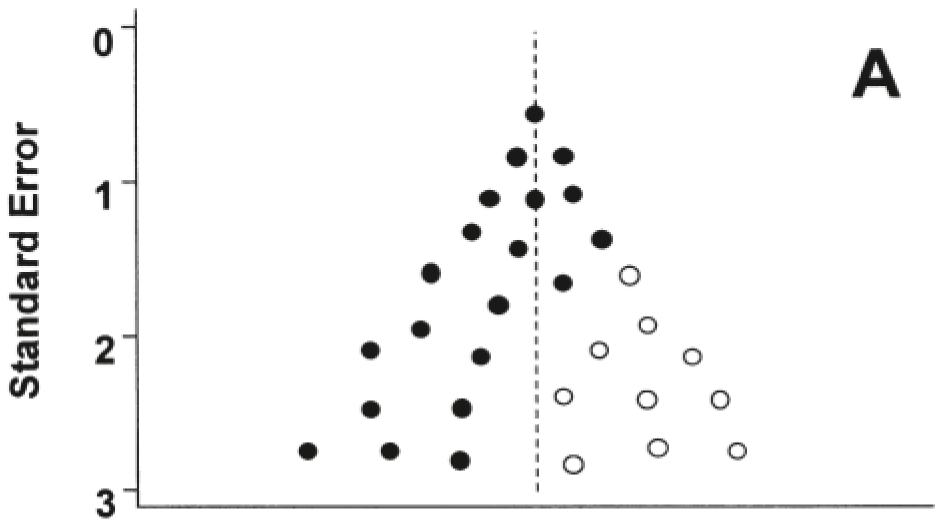
Several methods have been developed in order to detect the presence of publication bias: funnel plots, meta-significance tests and other parametric and non-parametric tools. (Stanley 2005) The following sub-chapters describe the main approaches to deal with publication bias in greater details.

3.2 Graphical approach

The basic approach to discover the presence of the publication bias is the visual examination of a funnel plot. It shows the non-standardized effect (regressions coefficients, estimated elasticities or correlation coefficients) on a horizontal axis. The vertical axis shows the precision, which can be measured in various ways: inverse of the standard errors (the most common and precise way according to Stanley (2005)), sample size or its square root, or number of degrees of freedom.

In the absence of publication bias studies with the results of high precision are plotted near the average while studies with the low precision results are spread on the sides of the average. It results in a funnel-shaped distribution with the center in the true population effect size (See Figure 3.1).

Figure 3.1: Hypothetical symmetrical funnel plot in the absence of bias

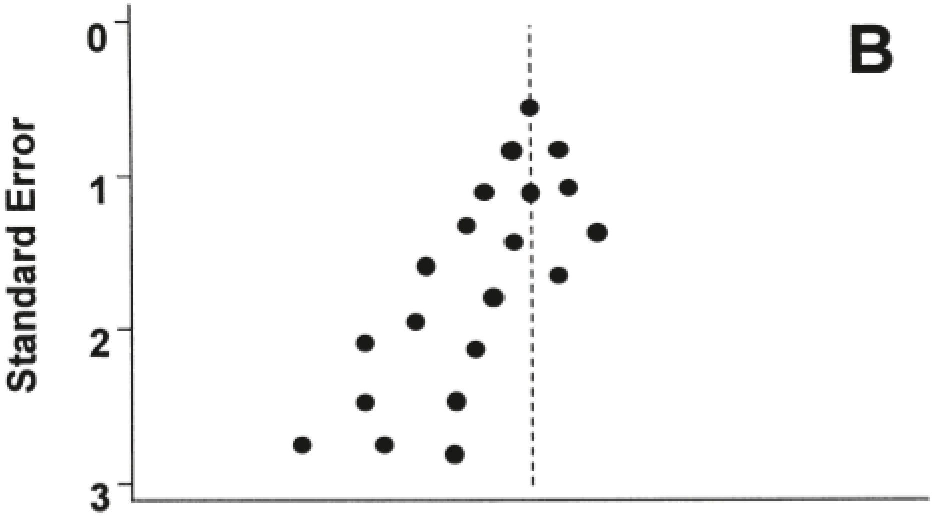


Note: Open circles indicate smaller studies showing no statistically significant effect. (Sterne & Egger (2001)).

Publication bias, however, assumes deviation from this shape and leads to asymmetric funnel plots, where one of the sides is "overweighted". The more distinct is the asymmetry, the more it is likely that the bias is substantial. Figure 3.2 shows one of the possible illustrations of the asymmetrical funnel plots.

It is important to note, though, that asymmetrical funnel plots need not

Figure 3.2: Hypothetical asymmetrical funnel plot in the presence of bias



Note: Smaller studies with no statistical significance are missing. (Sterne & Egger (2001))

necessarily arise from publication bias. There exist alternative explanations for the funnel plot asymmetry such as heterogeneity, selective outcome reporting and chance (Mavridis 2014). There usually exists heterogeneity of true effects across studies because of differences in data sets, countries or time periods used. Therefore, any asymmetric distribution of selected countries or time periods might cause the funnel plot's skewness. (Stanley 2005) Publication bias is thus not the only source of funnels' asymmetry and its validity can be called into question.

Galbraith plot can be an efficient way to examine heterogeneity in meta-analysis. It plots the individual standardized estimates on the vertical axis against reverse standard errors (precision) on the horizontal axis. It is basically a funnel plot rotated 90° and adjusted so as to remove its heteroscedasticity $effect_i/se_i$. In case of no genuine effect (discussed in a chapter below), the points should be randomly distributed around 0, with no systematic relation to precision. (Stanley 2005)

3.3 MRA tests: FAT-PET

Testing for publication bias is more precise and objective than visual inspection of plots. The so-called FAT (Egger *et al.* 1997) maybe considered as a test of a funnel plot's asymmetry. It involves running a regression between study's effect (it can be regression coefficients, estimated elasticities or correlation coefficients) and its standard error:

$$effect_i = \beta_0 + \beta_1 se_i + \sum_{k}^{K} \alpha_k Z_{j_k} + u_j \tag{3.1}$$

where β_0 stands for the "true" population value, β_1 measures publication bias, se_i is the standard error, Z_{j_k} is a set of other factors (e.g. number of observations) and u_j is the error term.

In case of no publication bias the estimate randomly varies around the true effect size (β_0) and is independent of the standard error. It is also worth mentioning that reported estimates in larger samples tend to approach the true effect β_0 (since standard errors decrease with the increased information). As a result, the publication bias approaches 0 with the error variance in large samples. Therefore, Stanley (2005) recommends to average the findings from only the largest studies (top 10%) in case of research areas containing vast numbers of primary studies.

Equation (2) is affected by heteroscedasticity, since the primary studies use different sample sizes, datasets and model selections. The standard error estimates will be biased in case heteroscedasticity is not corrected for. A way to deal with this problem is using weighted least squares (WLS) method, dividing the equation by the individual standard errors se_i, yielding:

$$effect_i/se_i = t_i = \beta_1 + \beta_0(1/se_i) + \sum_{k}^{K} \alpha_k Z_{j_k}(1/se_i) + v_i \tag{3.2}$$

where t_i is the conventional t-statistic associated with the effect from the primary studies. Inverse of the standard errors thus becomes a measure of residuals' heterosedasticity in the equation (3.1). Thanks to such weighting, precise results are considered more important (are given more weight) than less precise ones.

The inverse of the number of estimates in a study might be used as an alternative weighting scheme. Studies with many estimates are penalized and each study gains the same weight. This weight specification serves as a robustness check in our research.

The equation (3.2) provides the basis for running both FAT and PET (precision-effect test). The FAT becomes the t-test for the (3.2) equation intercept and may be now estimated with OLS, because the slope and intercept coefficients become reverse after the WLS procedure. While the FAT tests for the funnel plot's asymmetry and the presence of publication bias, PET tests for the presence of a genuine empirical effect beyond the bias of publication selection. The hypotheses of the tests are following:

FAT: H_0: $\beta_1 = 0$

PET: H_0: $\beta_0 = 0$

The bias and the genuine effect are present, if the null hypothesis of both tests is rejected.

3.4 Meta-regressions

The main traditional estimation methods applied in meta-analysis is fixed effects (FE) and mixed effects (ME) models.

As already mentioned in the previous chapter, the equation (3.2) is primarily estimated with OLS after the weighting procedure. However, there is a risk of arising structural dependency between the estimates within the same study or between the estimates of studies, which use the same methodology or data. To deal with this problem it is firstly worth clustering standard errors at study level. Secondly, FE should be applied; it deals with the estimates' dependency within an individual study and takes the form:

$$t_{i_j} = \beta_1 + \beta_0(1/se_{i_j}) + e_{i_j} \tag{3.3}$$

where i stands for an individual estimate and j stands for a particular study. Within FE all studies are assumed to share one common true effect size, with the observed effects distributed around it with a certain variance. All differences in observed effects arise due to sampling error. FE thus controls for unobserved heterogeneity arising due to differences in studies' data and methods.

As an alternative to FE, ME can be applied. Compared to FE, ME allows for the true effect size to differ across studies. It accounts for both within- and between-study variance. In its simplest form it approaches the data via a two-level model. One model describes the data at the study level, while the other explains the between-study variation in effects. However, ME is problematic since independent variables are often correlated with the study-level random effects, which contradicts ME's assumption.

The fixed-effects estimator is thus preferred to mixed-effects in this research. ME model is more common to use in case each study within a meta-analysis provides only one estimate, which is not satisfied in our case. Furthermore, ME approaches the heterogeneity issue but "at the cost of statistical power in identifying moderator effects." (De Dominicis *et al.* 2008)

3.5 Bayesian Model Averaging

Since there are many variables, which could potentially influence the dependent growth variable, the problems with model selection are likely to cause significant uncertainty, arising due to the probability of excluding relevant variables. Since the true set of independent variables in a regression is unknown, we have to deal with 2^K potential model specifications, where K denotes the total number of regressors in the model. It is obviously impossible to manually fit all specifications in order to find the best-fitting model. Bayesian Model Averaging (BMA) allows incorporating such model's uncertainty into inference and the resulting estimates thus reflect the true uncertainty. BMA starts with the following equation:

$$p(\Delta|Z) = \sum_{k=1}^{K} p(\Delta|Z, M_k)p(M_k, Z) \qquad M = (M_1, ..., M_k) \tag{3.4}$$

where M is the set of considered models and $p(\Delta|Z)$ is the posterior distribution of Δ (which is a parameter of interest, such as a future observable or a model parameter) given data Z.

With the help of Bayesian model averaging we can fit a lot of models determined by available set of regressors and find the weighted average of these regressions. (Zeugner 2011) These weights are called posterior model probabilities (PMPs). The posterior probability for model M_k is computed as follows:

$$p(M_k|Z) = \frac{p(Z, M_k)p(M_k)}{\sum_{m=1}^{K} p(Z|M_m)p(M_m)} \tag{3.5}$$

where

$$p(Z|M_k) = \int \dots \int p(Z|\theta_k, M_k)p(\theta_k|M_k)d\theta_k \tag{3.6}$$

Equation (7) is a marginal likelihood of model M_k, θ_k is the parameter vector, $p(Z|\theta_k, M_k)$ is the likelihood and $p(\theta_k|M_k)$ is a prior density of parameters. The application of the above equations yields the parameter estimates. The BMA estimate of a parameter θ is:

$$\hat{\theta} = \sum_{k=1}^{K} \hat{\theta}_k p(M_k|Z) \tag{3.7}$$

where $\hat{\theta_k}$ is the posterior mean for model k.

This is the final prediction we get after BMA weights every individual forecast by its posterior model probability. BMA basically computes a weighted average of individual regressions with various sets of independent variables. PMPs serve as a measure of model's fit - they can be perceived as an R-squared, which measures how well observed outcomes are replicated by the model. The models, which fit the data most precisely, receive the highest PMPs. PMPs of all regressions including the specific variable sum up to a so-called posterior inclusion probability (PIP), which is a measure allowing to see whether a certain variable should be included in the true model.

The BMA's regression output reports three statistics: posterior mean, posterior standard deviation and PIP for every explanatory variable in question. The posterior mean can be perceived as an estimate coefficient from a linear regression, since it explores how this particular independent variable affects the target. Posterior standard deviation is comparable to the standard error and PIP is analogous to frequentist statistical significance. Hoeting *et al.* (1999) and Koop *et al.* (2007) provide with the more detailed theoretical introduction to the BMA approach.

In practice, the bms package in R should be applied to perform bayesian model sampling, since it demands a great degree of computation. It samples data according to various model priors and allows choosing different samplers. Zeugner *et al.* (2015) paper is a valuable guide on the BMA's application in R. They apply the Metropolis-Hastings algorithm, which is a Markov chain Monte Carlo (MCMC) approach, allowing to compute a sequence of random samples from a complicated probability distribution. Markov chain is a powerful tool of a stochastic nature, which is able to compute huge hierarchical models by integrating over an enormous amount of unknown parameters. The Metropolis-

Hastings algorithm randomly "walks" through the pool of possible models and chooses the model with the highest PMP through Markov chain Monte Carlo samplers.

3.6 Criticism of the Meta-Analytical approach

The tendency to criticize meta-analysis has increased in the past years since the number of meta-analytical works is growing rapidly with the meta-analyses of meta-analyses now being published. This section addresses the most common points of criticism. For more detailed information on the topic see Havranek & Irsova (2017) and Stanley (2001; 2005; 2013).

The major criticism primarily regards the difficulty and complexity of data collection when conducting the meta-analysis, since most mistakes are likely to take place particularly at this stage of research. The primary studies are heterogenous in their choice of analyzed data, econometric methods, choice of explanatory variables etc. The authors of primary literature can often use the same regression specification but different variables' units. For example, the dependent variable may be taken in a logarithmic form or in levels. Alternatively, some studies may focus on the elasticity of estimates, while others may define the effect size in a different way. If this is not considered and the data is not properly adjusted, the results are incomparable and meta-analysis in such a case is meaningless.

Our dataset excludes all studies with irrelevant or incomparable results, even though some of them directly relate to the topic, to ensure the maximum possible homogeneity of data. The criteria for studies' inclusion in the dataset are stated in Section 4.1. Even by ensuring the comparability of estimates included in the meta-sample, the heterogeneity in the data can't be fully avoided though. We therefore apply the BMA regression to control for heterogeneity. We include 40 variables describing the characteristics of primary studies' data and methodology in the regression to better explain the variability of results and resolve the model's uncertainty.

Another point of meta-analysis criticism relates to the possible poor-quality of primary literature. Though fighting for objectivity, meta-analysts often use data from studies without examining their quality. (Glass 1976) A large number of low-quality studies lead to unreliable meta-analytical results since the dataset is contaminated. Our dataset is composed of journals and both published and unpublished working papers since we try to include as many studies as possible in our research. We are using the weighting method in order to assign more significance to studies which are more precise. Furthermore, the majority of data in our dataset is taken from a previously published in a journal meta-analysis by other researches (De Dominicis *et al.* 2008), which decreases the chances of high amount of low-quality estimates arising in the sample.

Chapter 4

Empirical research

The following chapter provides with the description of the data used in the present research, graphs' investigation and tests results and presents the main findings. The first section is devoted to the summary of the data collection process. The criteria for studies' inclusion in the dataset are stated. The main characteristics of data are summarized by both simple and weighted means of primary estimates, and visualized with the help of histograms and plots. Potential publication bias is then inspected with the help of visual examination of a funnel plot and regression tests. As the last step of the analysis I implement BMA model in order to inspect heterogeneity arising from the differences in primary studies. To check the robustness of the results I finally apply frequentist check of the BMA exercise.

4.1 Data

The existing dataset of 37 studies composed by De Dominicis *et al.* (2008) serves as the foundation for the research conducted in the paper. Additional primary studies were collected during a 3-months period, starting from October 2017 till the end of December 2017. Purely narrative or summarizing studies were excluded from the research.

Initially, 59 empirical studies were found when using "Economic Inequality Growth" as a main search keyword. The search was restricted to the academic papers written solely in English after the year 2008. The electronic libraries for the literature search included the following portals: (1) Charles University E-resources Portal, (2) EBSCOhost, (3) GoogleScholar, (4) ScienceDirect, (5) Springer, (6) JSTOR, (7) ResearchGate.

Out of 59 initially found studies only 21 were included in the final dataset. 38 papers didn't fulfill the criteria to be included in the analysis for different reasons: majority of the literature had a different incomparable perspective on the issue or used unconventional estimation methods. The major criteria for the study's inclusion were: (1) the presence of a defined coefficient of income inequality effect on GDP growth, (2) a reported standard error (or a statistic, from which it can be computed), (3) the use of a Gini coefficient as a measure of income inequality, (4) assumed linear relationship between income inequality and GDP growth.

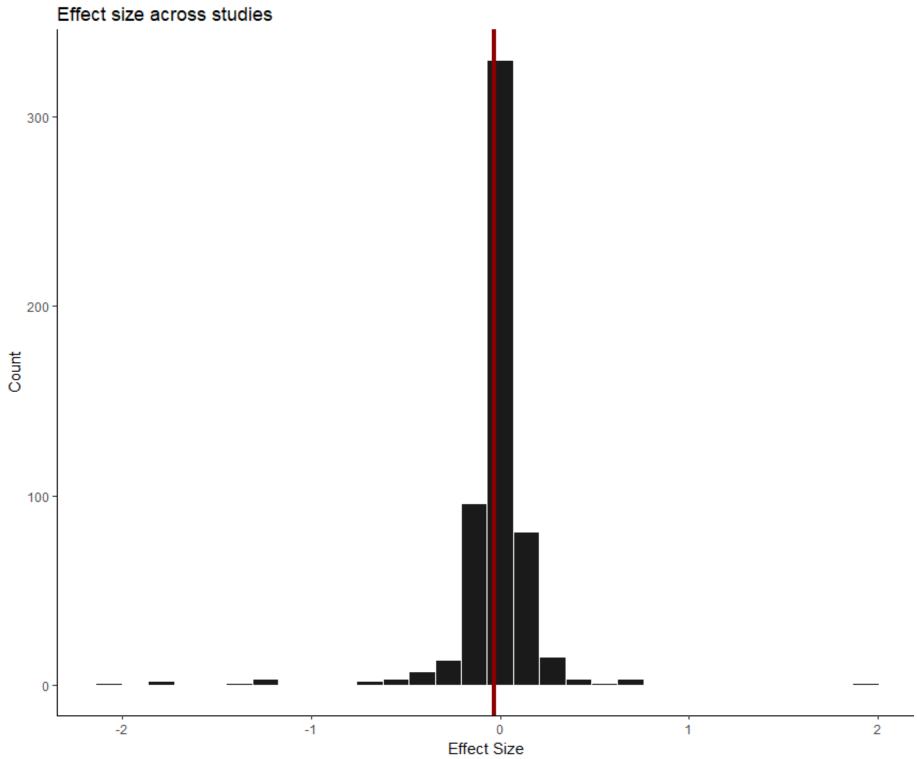
The final dataset is thus composed of 58 studies (see Apendix A) and 562 coefficient estimates - effect sizes. The effect size is defined as a partial derivative of the average annual growth rate (measured on a percentage basis) with respect to the Gini coefficient (measured on a unit basis). The effect size thus reflects how a one-unit point change in the Gini coefficient influences the average annual growth rate measured as a percentage. For example, an effect size of -0.3 implies that an increase in Gini from 0.01 to 0.02 (1 Gini point) will result in a 0.3% decrease in the average annual growth rate. Some estimates from the primary literature had to be transformed since they were not always comparable.

Figure 4.1 presents a histogram of the estimated coefficients of inequality on GDP growth. Approximately 64% of reported estimates are negative (359 out of 562), while 36% (203) are positive. The mean and median estimates are almost equal with the mean of the value -0.0304 and median of -0.03. The histogram's shape indicates the presence of outliers among the values. By winsorizing the data on standard errors at 1% on both distribution's sides I get rid of extreme values. Figure 4.2 depicts the distribution of estimates without the presence of outliers. It is clearly seen that 98% of estimates lie between values -0.2 and 0.1.

The majority of primary studies (38 studies) are journals while 20 are working papers. 41 studies were published before the crisis of 2008. 31 studies work with cross-section data only (from which the majority are studies published before the crisis) while 33 sources rely solely on panel data (mostly recent studies). 8 studies use both types of data and 2 studies are based on time-series analysis.

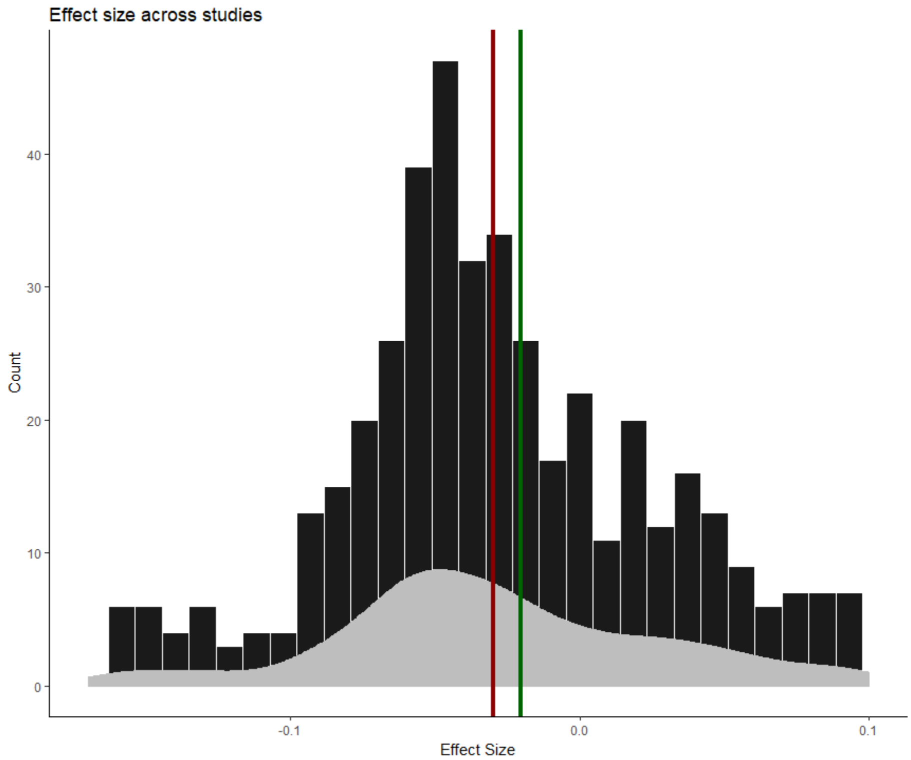
The heterogeneity between and within the individual studies can be well detected by the box plot, which illustrates the minimum, first quartile, median, third quartile, and maximum of each study's estimate. The vertical line within each box represents the median. Outliers are depicted by dots. Box

Figure 4.1: Inequality on growth effects distribution



Note: The figure represents the distribution of inequality on GDP growth effect estimates reported in primary studies. The solid vertical red line represents both the mean and the median of all the estimates. The histogram contains extreme values.

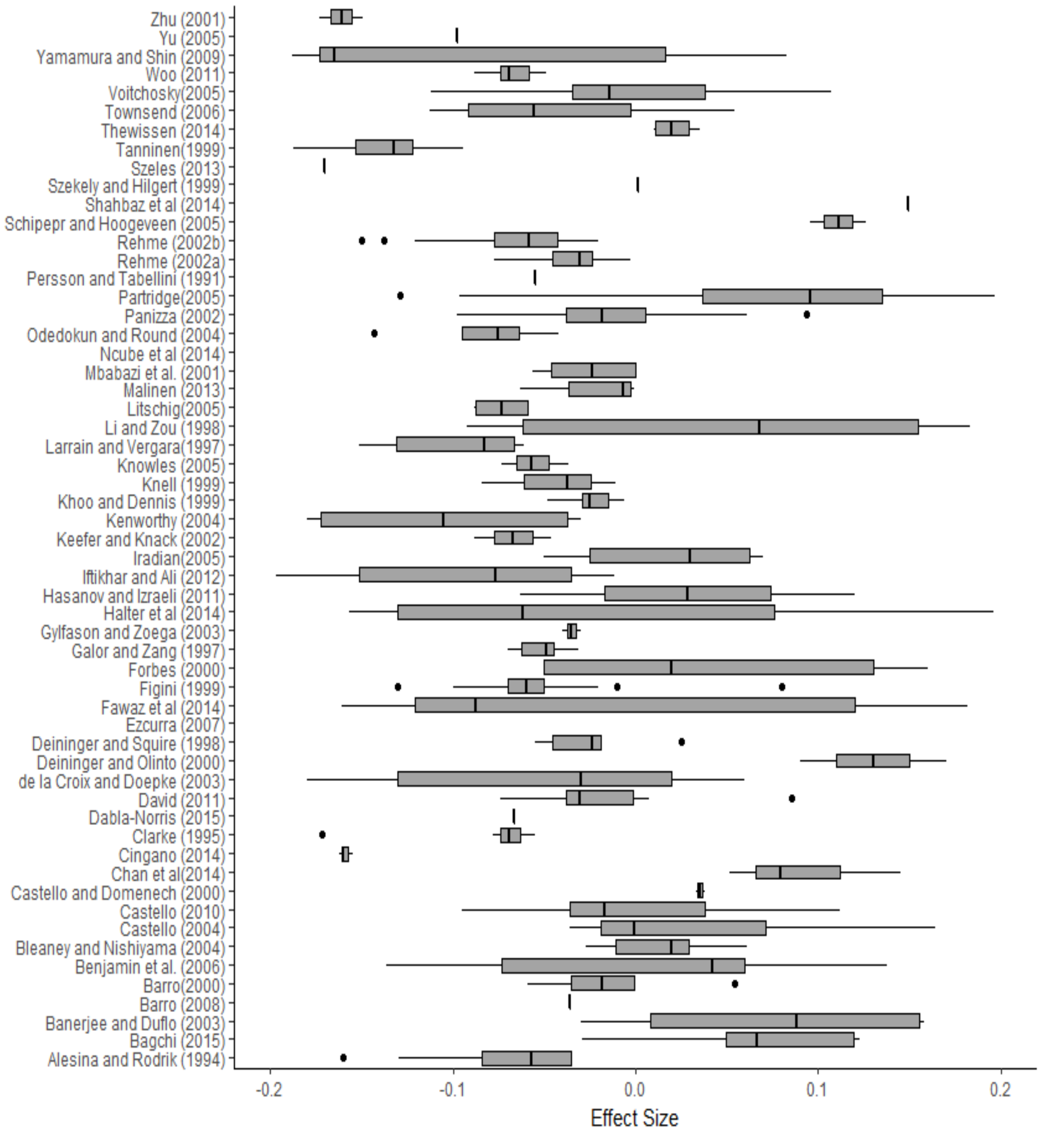
Figure 4.2: Winsorized inequality on growth effects distribution



Note: The figure represents the distribution of inequality on GDP growth effect estimates reported in primary studies without the presence of outliers. The solid vertical red line represents the median of all the estimates. The solid vertical green line represents the mean of all the estimates. The grey area represents the distribution's density.

plots are a helpful way to visualize the characteristics of responses for a certain group of estimates. Majority of the studies in question report negative estimates between -0.1 and 0. (see Figure 4.3) Both between and within-study heterogeneity is substantial.

Figure 4.3: The division of inequality on GDP growth effects



Note: The figure depicts a box plot of the estimates of inequality on GDP growth effect reported in primary studies. Outlying values are removed for better visual presentation. The box indicates interquartile range. The median is represented by the vertical line. Individual dots depict outliers.

Tables 4.1 - 4.4 below present the mean estimates and a 95% confidence interval (with the standard errors clustered at study level) for certain groups of variables, divided by different criteria. The statistics are provided on a winsorized effect size sample so as not to bias the results by the outlying values. The left-hand side of the table depicts unweighted results while on the right-hand side the estimates are weighted by the inverse of the number of estimates reported per study. I adopt the weighting method from Havranek & Irsova (2017) paper, according to which each study is assigned the same importance. The full description of all mentioned variables can be found in the Table 4.7 in the section 4.4. The results suggest differences in the estimates' values depending on the estimation methods, considered country groups, type of data and used inequality databases.

Table 4.1: Inequality on GDP growth effects across different paper type/data used

	Unweighted				Weighted		
	No. of est.	Mean	95% conf. int.		Mean	95% conf. int.	
Publication date = 1	423	-0.027	-0.063	0.010	-0.074	-0.140	-0.009
Publication date = 0	139	-0.043	-0.095	0.009	-0.075	-0.153	0.003
Publication type = 1	165	-0.071	-0.129	-0.014	-0.162	-0.298	-0.025
Publication type = 0	397	-0.014	-0.047	0.019	-0.032	-0.062	-0.002
Cross-section	273	-0.054	-0.085	-0.023	-0.081	-0.123	-0.039
Pooled	287	-0.009	-0.054	0.035	-0.073	-0.161	0.014
High-quality Gini	333	-0.012	-0.050	0.025	-0.036	-0.068	-0.004
Low-quality Gini	38	-0.102	-0.214	0.010	-0.182	-0.403	0.039
High&low-quality Gini	184	-0.055	-0.107	-0.004	-0.107	-0.219	0.006
Gini type = 1	371	-0.022	-0.057	0.013	-0.044	-0.084	-0.004
Gini type = 0	191	-0.048	-0.102	0.007	-0.115	-0.220	-0.011
Gini on income	402	-0.040	-0.078	-0.001	-0.083	-0.144	-0.021
Gini on expenditure	8	-0.350	-0.625	-0.074	-0.449	-0.655	-0.243
Gini adjusted	152	0.009	-0.027	0.046	-0.009	-0.068	0.049
Other inequalities = 1	125	0.026	-0.029	0.080	-0.017	-0.094	0.060
Other inequalities = 0	437	-0.047	-0.075	-0.018	-0.084	-0.139	-0.028
ALL	562	-0.031	-0.061	0.000	-0.075	-0.126	-0.023

Note: The table presents the mean estimates of the inequality on GDP growth effects for a particular type of study and data used in a study. Variables are described in detail in the Table 4.7 in the section 4.4. The confidence intervals around the mean are constructed using standard errors clustered at study level. On the right-hand side are the estimates weighted by the inverse of the number of estimates reported per study (clustering and weights methods are based on Havranek & Irsova (2017))

The results in Table 4.1 suggest on average higher negative coefficients reported in unpublished working papers than in journals. Same pattern is visible when comparing studies relying on cross-section data with those based on panel data analysis.

The Gini coefficient of high quality yields on average less negative estimates, compared to scenarios of low-quality and both low & high-quality Gini. Speaking about Gini quality, to be considered high-quality the data on inequality should fulfill certain criteria according to Deininger and Squire (1996). It must be based on household surveys, the surveyed population sample should represent the entire country average and the income measure must be comprised from various sources of income including self-employment, non-wage revenues etc. The authors of primary studies usually precised the quality of used data, however, when they didn't, we automatically assumed the data to be of low quality.

Gini can be measured in various ways: based on data on income (pre-tax or post-tax) or expenditure. Furthermore, data can be aggregated on individual or household level. This incomparability of data often led the authors of primary studies to use data with different specifications, which can cause potentially serious problems. For instance, inequality values based on expenditure data are likely to be lower than if based on income. Some authors therefore transformed their inequality data to increase the level of comparability. They adjusted their data according to the Deininger and Squire (1996) method, who suggest adding 6.6 points to the indexes based on expenditure rather than income. We thus record three categories of Gini used in primary studies: Gini based on various income definitions, Gini based on expenditure and Gini adjusted by DS method.

Table 4.1 suggests that the adjusted Gini produces positive effect size estimates, compared to other Gini specifications. When weighted, though, (which is more reliable) all specifications yield negative results. The coefficient of Gini based on expenditure is significantly higher in magnitude than if based on income or adjusted.

If inequalities other than income (human capital, land ownership inequality) are included in a primary study's regression the mean estimate tends to be positive. When weighted, though, all mean estimates turn out to be negative.

One of the goals of this thesis is to find out whether the average reported coefficient in papers published before crisis differs from the one in papers published after crisis. The one would expect the resulting estimates to have different signs since the after-crisis pessimistic sentiments could have likely induced the authors to be in favor of negative outcomes. According to obtained results in Table 4.1, the period of paper's publication doesn't seem to largely affect the average coefficient. Mean estimates of both time samples are negative and studies published after crisis are only slightly more negative, especially in a weighted specification. However, this still confirms our hypothesis, stating that "The average resulting coefficient is higher and negative in the papers published after the global financial crisis of 2007-2008."

Table 4.2 presents the division of variables geographically - based on country groups. The mean estimate is lowest for developing countries in an unweighted specification and for OECD countries, when the estimates are weighted. Analysis on regional level yields slightly lower (unweighted case) and significantly lower (weighted case) mean effect than in case of country level analysis.

Table 4.3 depicts the estimates' division based on databases used in primary studies. Majority of studies rely on Deininger & Squire (1996) database, which yields the highest average effect size estimate. If other than high-quality Deininger & Squire (1996) database is used, the mean estimate is much more negative.

Table 4.2: Inequality on GDP growth effects vary geographically

	Unweighted				Weighted		
	No. of est.	Mean	95% conf. int.		Mean	95% conf. int.	
OECD sample	196	-0.028	-0.099	0.042	-0.140	-0.283	0.002
LDC sample	71	-0.057	-0.124	0.011	-0.116	-0.266	0.034
OECD&LDC sample	295	-0.026	-0.056	0.004	-0.055	-0.055	-0.002
Country level	434	-0.024	-0.047	-0.002	-0.043	-0.075	-0.011
Regional level	128	-0.052	-0.172	0.067	-0.214	-0.434	0.005
ALL	562	-0.031	-0.061	0.000	-0.075	-0.126	-0.023

Note: The table presents the mean estimates of the inequality on GDP growth effects for a particular country group and depending whether the primary analysis was done at country or regional level. Variables are described in detail in the Table 4.7 in the section 4.4. The confidence intervals around the mean are constructed using standard errors clustered at study level. On the right-hand side are the estimates weighted by the inverse of the number of estimates reported per study (clustering and weights method are based on Havranek & Irsova (2017))

According to results in Table 4.4 only FE and RE estimation methods produce positive mean estimates, while others yield negative average effect. Simultaneous systems and other estimations methods (including time-series analysis, MLE and FGLS) induce the most negative mean results.

Table 4.5 depicts the estimates of inequality on GDP growth effects based on certain control variables used in the regressions in primary literature. We can see that GDP per capita is the most commonly included independent variable, used in 93% of the primary analyses. It is followed by the incorporation of

Table 4.3: Inequality on GDP growth effects across different databases

	Unweighted				Weighted	
	No. of est.	Mean	95% conf. int.		Mean	95% conf. int.	
D&S data	196	-0.018	-0.059	0.024	-0.011	-0.047	0.026
Jain data	19	-0.074	-0.081	-0.066	-0.075	-0.084	-0.067
Lis data	45	-0.046	-0.091	-0.001	-0.066	-0.140	0.008
Wiid data	109	-0.032	-0.087	0.022	-0.078	-0.138	-0.017
Other data	193	-0.036	-0.108	0.036	-0.127	-0.240	-0.014
ALL	562	-0.031	-0.061	0.000	-0.075	-0.126	-0.023

Note: The table presents the mean estimates of the inequality on GDP growth effects for a particular inequality database used in primary studies. Variables are described in detail in the Table 4.7 in the section 4.4. The confidence intervals around the mean are constructed using standard errors clustered at study level. On the right-hand side are the estimates weighted by the inverse of the number of estimates reported per study (clustering and weights method are based on Havranek & Irsova (2017))

Table 4.4: Inequality on GDP growth effects across different estimation methods

	Unweighted				Weighted		
	No. of est.	Mean	95% conf. int.		Mean	95% conf. int.	
OLS	277	-0.041	-0.073	-0.009	-0.082	-0.127	-0.037
FE	103	0.038	-0.008	0.085	0.024	-0.030	0.079
RE	25	0.048	0.005	0.092	0.026	-0.006	0.059
GMM	111	-0.028	-0.073	0.018	-0.026	-0.075	0.022
Simultaneous	30	-0.151	-0.276	-0.026	-0.140	-0.268	-0.013
Other estimations	12	-0.344	-0.863	0.176	-0.354	-0.834	0.126
ALL	562	-0.031	-0.061	0.000	-0.075	-0.126	-0.023

Note: The table presents the mean estimates of the inequality on GDP growth effects based on a particular estimation method implemented in primary studies. Variables are described in detail in the Table 4.7 in the section 4.4. The confidence intervals around the mean are constructed using standard errors clustered at study level. On the right-hand side are the estimates weighted by the inverse of the number of estimates reported per study (clustering and weights method are based on Havranek & Irsova (2017)) an education measure (accounting for male or female education enrollment or both) in the regression. Both variables though don't drastically change the mean results. The inclusion of the democracy dummy and the price level for investment measure switch the sign of the mean estimate to positive.

If country effects (country dummies, country-based subsamples) are accounted for in the studies, the mean effect estimate of the unweighted regression is almost non-negative. When weighted, though, the coefficient gains more magnitude.

Table 4.5: Inequality on GDP growth effects across different control variables

	Unweighted				Weighted		
	No. of est.	Mean	95% conf. int.		Mean	95% conf. int.	
Country dummies	110	-0.002	-0.078	0.075	-0.066	-0.180	0.049
Education	323	-0.051	-0.091	-0.011	-0.103	-0.174	-0.032
Institutions	51	-0.017	-0.054	0.020	-0.062	-0.131	0.006
GDP per capita	523	-0.020	-0.049	0.008	-0.058	-0.102	-0.014
Investment	175	-0.050	-0.071	-0.029	-0.078	-0.128	-0.028
Democracy	59	0.018	-0.005	0.041	0.019	-0.018	0.057
X	82	-0.004	-0.041	0.033	-0.058	-0.139	0.022
Human capital	106	-0.019	-0.057	0.020	-0.013	-0.072	0.047
G	112	-0.023	-0.066	0.020	-0.057	-0.108	-0.005
PPI	81	-0.009	-0.082	0.064	0.002	-0.053	0.057
Fertility	66	-0.067	-0.133	-0.001	-0.115	-0.244	0.013
ALL	562	-0.031	-0.061	0.000	-0.075	-0.126	-0.023

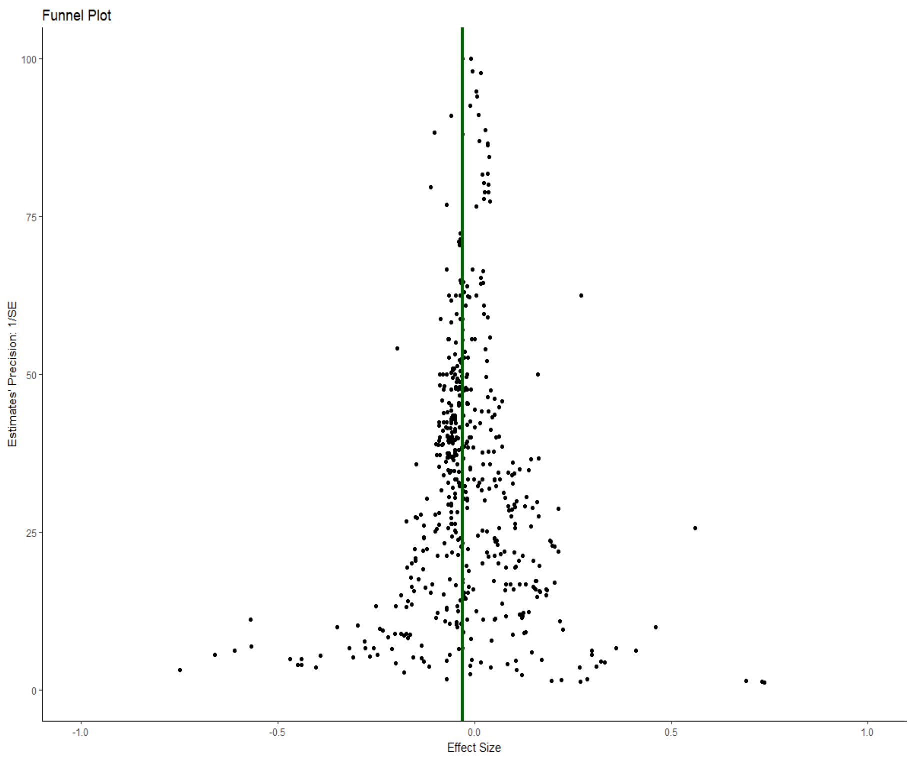
Note: The table presents the mean estimates of the inequality on GDP growth effects based on a particular control variable included in the primary studies' regression. Variables are described in detail in the Table 4.7 in the section 4.4. The confidence intervals around the mean are constructed using standard errors clustered at study level. On the right-hand side are the estimates weighted by the inverse of the number of estimates reported per study (clustering and weights method are based on Havranek & Irsova (2017))

4.2 Publication bias: graphical approach

As already mentioned in the methodology section, funnel plot serves as a tool for visual examination of publication bias presence. In case of no bias the plot presents an inverted funnel-shaped distribution with the most precise estimates centered around the "true" value. Figure 4.4 shows the funnel plot of the inequality on GDP growth effect estimates. The horizontal axis depicts the effect sizes from primary studies, while the vertical axis presents precision (inverted standard errors are used as proxy). Precision can be as well measured by number of observations reported in each primary study. This, however, doesn't seem to be a perfect approach since data aggregation methods differ across studies, which might be difficult to explain.

For better visual examination I removed 32 observations with extreme precision or effect size values. Nevertheless, in the statistical tests conducted in the next chapter I include all the estimates without any exclusion. A solid vertical green line on the plot indicates a mean and median value of effect estimates including the extreme observations, which are not plotted.

Figure 4.4: Funnel plot of effect size estimates without outliers

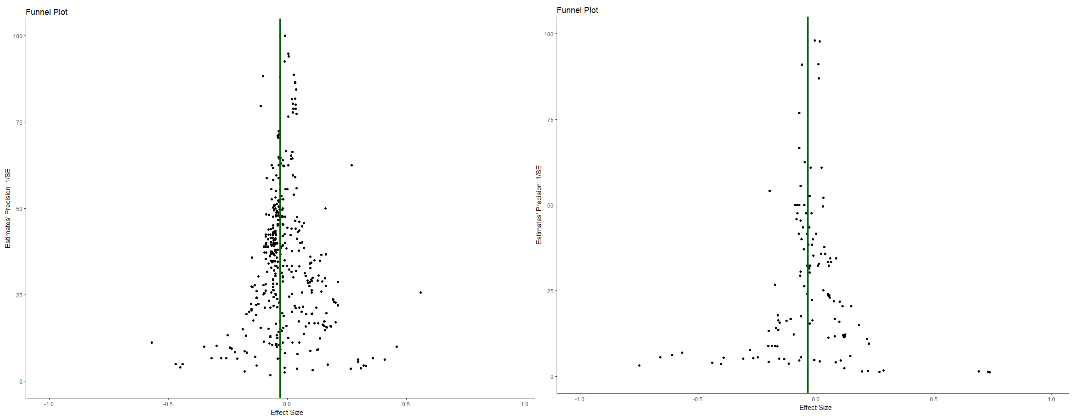


Note: The figure depicts a funnel plot of inequality on GDP growth effect estimates reported in primary studies. The solid vertical green line represents the mean and median of all the estimates. Observations with extreme precision values and effect size values are excluded for better graphical exposition. They are, however, included in the statistical tests.

Figure 4.5 captures the funnel plots of estimates from primary studies pubished (a) before the crisis of 2008 and (b) after the crisis of 2008. Observations with extreme precision and effect size values are again excluded for better graphical exposition. The first plot is thus constructed out of 397 (423-26) effect size estimates, the second one out of 133 (139-6) estimates.

Figure 4.5: Funnel plots of effect size estimates for two time samples

(a) Before crisis (b) After crisis



Note: The figure depicts funnel plots of inequality on GDP growth effect estimates reported in primary studies published (a) before crisis and (b) after crisis. The solid vertical green line represents the mean and median of all estimates within the time sample. Observations with extreme precision values and effect size values are excluded for better graphical exposition. They are, however, included in the statistical tests.

The funnel plot allows to make preliminary judgments about the presence of publication bias prior to conducting tests. Firstly, an asymmetric plot without a funnel shape can be a sign of eliminated estimates (of certain magnitude or sign) by authors of primary literature. The constructed inequality on GDP growth effects plot has a desired funnel shape, though the left side looks slightly heavier. The negative values outnumber the positive ones, which might suggest the predisposition of authors to publish results with negative coefficients.

Secondly, multiple plot's peaks are a sign of heterogeneity in the estimated effects, which results into several relatively precise "true" effect values. This is often the case in meta-analysis, since primary studies rely on different data. In our case there is only one clearly visible peak, though there are some individual outliers on the top part of the plot.

Lastly, hollow funnel plots are a sign that there are not many reported estimates with low precision in the primary studies. This is indeed the presented case. The lower part of the graph looks hollow, which might suggest that authors tend to publish significant estimates.

The plots which split the estimates according to the time of publishing (Figure 4.5) do not reveal any striking observations. Both plots are symmetrical. Plot (b) with the later published papers, however, looks more desirable than its counterpart. It is not overwhelmed on the left side with the negative estimates and there are no outlying values that would create additional multiple peaks.

To conclude, even though we can observe slight indicators of possible publication bias in the reported figure, typical funnel plots in economics meta-analyses exhibit much more distinct signs of publication bias. A funnel plot is a merely subjective visual judgment of the relationship between the estimates and their precision. As Stanley (2005) justly remarked, "symmetry may be more in the eye of the beholder than the actual research record itself". Furthermore, publication bias is only one of possible reasons of funnel plot's asymmetry. We thus proceed with the investigation of the publication bias presence by means of conducting statistical tests.

4.3 Publication bias: FAT-PET

Testing for funnel plot's asymmetry provides with more precise and reliable results concerning the presence of publication bias. Estimate coefficients are randomly distributed around the true effect size and are independent of their standard errors in case of no publication bias. The equation (2) from the chapter 3.3. can be customized for our case in the following way:

$$Effect\ size_{i_j} = Effect\ size_0 + \beta * SE(Effect\ size_{i_j}) + \omega_{i_j} \tag{4.1}$$

where $Effect\ size_{i_j}$ stands for i-th estimates of the inequality on GDP growth effect found in the j-th study, $SE(Effect\ size_{i_j})$ stands for standard errors of the estimated effect sizes, $Effect\ size_0$ is a mean inequality on GDP growth effect estimate corrected for possible publication bias, β measures publication bias and ω_{i_j} denotes disturbances.

I estimate the above equation using several methods. The results are provided in the Table 4.6. The test is conducted in two ways: by means of unweighted and weighted regressions. Standard errors are clustered at study level in order to maintain robustness since the regression (9) is heteroscedastic. Panel A of Table 4.6 presenting unweighted regressions has 3 columns, which are defined as follows:

1. All estimates are included in the regression,

2. Only estimates from the studies published before the crisis of 2008 are included in the regression,

3. Only estimates from the studies published after the crisis of 2008 are included in the regression.

Panel A estimates are obtained with OLS regression. However, since our data is much unbalanced and heterogeneous due to different variables, time horizons and number of estimates considered in primary studies, it is more appropriate to use fixed effects method. Panel B and C describe the results of FE and RE estimation methods accordingly. RE serves as a robustness check. Panel D presents the results of the instrumental variable approach. The columns are divided the same way as in Panel A.

Panel E depicts the results of the weighted regressions for all three time samples. Since equation (9) is heteroscedastic it is a common practice in meta-analyses to divide the equation by corresponding standard error, thus assigning greater importance to precise results. Apart from this weighting by precision, weights can be assigned by the inverse of the number of estimates reported in primary studies. Each study thus receives an equal weight = importance. The columns in Panel E for each group of estimates are divided as follows:

1. All estimates weighted by their precision ($1/SE$) are included in the regression,

2. All estimates, weighted by the inverse of the number of estimates from primary studies (in addition to the previous weight), are included in the regression.

The results of the conducted tests vary depending on the considered sample of studies. When only studies published before the Lehman Fall of 2008 are taken into account, the bias is confirmed with the p-value signicant at a 1% level in 3 out of 4 considered estimation methods. The null hypothesis of no publication bias H_0: $\beta_1 = 0$ is rejected (see Methodology part). Biased coefficients of these methods are negative and close to each other in value proving the existence of authors' bias towards the negative effects of inequality on growth. Test's results for earlier studies support some observations from the funnel plot, which is overweighted to the left and has hollows. There exists a bias in favour of negative and significant estimates.

When we conduct the test on a sample of new studies, published after the crisis of 2008 the bias is confirmed in 2 out of 4 specifications. Interestingly,

Table 4.6: FAT/PET

A: Unweighted regressions (OLS)	All estimates	Before crisis	After crisis
SE (publication bias)	-0.2987	-0.9086***	0.4863
	(0.3728)	(0.1668)	(0.3142)
Constant (effect beyond bias)	-0.0084	0.0238	-0.0942*
	(0.0272)	(0.0155)	(0.0557)
Observations	562	423	139

B: Unweighted regressions (FE)	All estimates	Before crisis	After crisis
SE (publication bias)	0.1429	-0.8018***	1.3422***
	(0.6655)	(0.2413)	(0.3627)
Constant (effect beyond bias)	-0.0410	0.0176	-0.1985***
	(0.0492)	(0.0140)	(0.0442)
Observations	562	423	139

C: Unweighted regressions (RE)	All estimates	Before crisis	After crisis
SE (publication bias)	-0.0627	-0.8338***	0.7044**
	(0.5698)	(0.2006)	(0.3301)
Constant (effect beyond bias)	-0.0575	-0.0130	-0.1251*
	(0.0465)	(0.0266)	(0.0641)
Observations	562	423	139

D: Unweighted regressions (IV)	All estimates	Before crisis	After crisis
SE (publication bias)	0.0363	0.5384	-0.5963
	(0.5561)	(1.8075)	(0.4429)
Constant (effect beyond bias)	-0.0331	-0.0602	0.0377
	(0.0382)	(0.0943)	(0.0623)
Observations	562	423	139

E: Weighted regressions	All Estimates		Before crisis		After crisis	
	Precision	Study	Precision	Study	Precision	Study
SE(publication bias)	-0.3702**	-0.7835***	-0.4834*	-1.0109***	-0.1314	-0.3491
	(0.1771)	(0.2847)	(0.2942)	(0.3652)	(0.1399)	(0.3463)
Constant (effect beyond bias)	-0.0031	-0.061	-0.0008	-0.0031	-0.0189	-0.0229*
	(0.0041)	(0.0052)	(0.0036)	(0.0050)	(0.0137)	(0.0143)
Observations	562	562	423	423	139	139

Note: Standard errors are in parentheses. Standard errors are clustered at study level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

positive biased coefficients in FE and RE differ in sign from negative true effects. FE's biased coefficient's value (exceeding one) is sufficiently higher than all compared values. Constants' values, though not high in magnitude, are significant and negative in all models for the sample of new studies.

When all estimates are considered together regardless of the timespan horizon, the overall intuition from the visual funnel plot's inspection is confirmed. There is no evidence of genuine effect presence; we are not able to reject the null hypothesis of no publication bias in any specification. When weighted though, the genuine effect proves to be present (particularly in earlier published studies, which is in line with unweighted results for this group). We believe weighted regressions to be more reliable than the unweighted ones since they correct for heteroscedasticity.

Generally, FAT/PET results suggest little evidence of the effect of inequality on GDP growth. Only coefficients from recent studies are significant, while all other specifications assume no underlying effect.

4.4 Determinants of heterogeneity

Bayesian Model Averaging method is a way to address heterogeneity of inequality on GDP growth effect estimates from primary studies. It will help us to determine what drives differences between the reported effect coefficients. Since our model contains a large number of regressors (40 explanatory variables), the number of possible model specifications results into 2^{40}. This presents uncertainty which model to choose in order to explain the heterogeneity of primary literature's results. Computing manually all 2^{40} options is certainly not practical, while ignoring model's uncertainty is suboptimal. We thus rely on Monte Carlo Markov Chain algorithm by using the bms package in R.

We choose the bms function's properties as follows:

- *mprior = 'uniform'*
  We set the model prior probability to *'uniform'* following the Zeugner (2011) guide to bms package. A uniform prior basically means that a prior probability is a constant function and that all possible model's values are equally likely *'a priori'*.

- *g = 'UIP'*
  g stands for a constant and, if set to *'UIP'* it is equal to the number of observations (562 in our case).

- *mcmc = 'bd'*
  The above parameter stands for the Markov Chain Monte Carlo sampler. We set it to be equal to *'bd'* (birth-death algorithm), since it is a standard procedure used in most BMAs. (Zeugner (2011)) Within this algorithm one of the potential variables is randomly chosen from the sampler. If the chosen variable is already a part of the current model, it will be dropped; if not, it will be added.

- *iter = 2 000 000*
  The overall number of iterations to be sampled is set to be 2 million.

- *burn = 1 000 000*
  We set the number of burn-ins (number of iterations that are not stored to compute PMPs) to 1 million.

- *nmodel = 5 000*
  This parameter stands for the number of the best-fitting models, for which information is stored. We set the number of best models to 5000 (not to slow down the sampler by the bigger value).

The results of BMA in case of alternative bms function's properties are presented in the Appendix B.

Figure 4.6 presents the results of the conducted BMA analysis on the winsorized sample (at 1% on both distribution's sides) of effect size estimates. All included in the regression explanatory variables are depicted on the vertical axis. The full list of variables in the research and their description is provided below in Table 4.7. From 45 moderator variables I exclude 5 variables (time_series, gini_adj, oecdldc, country, jain) from the BMA regression since they prove to be highly correlated with the other variables. This finally leaves us with 40 variables plotted on the vertical axis of the BMA plot. The correlation matrix of those 40 regressors is presented in Appendix C.

The horizontal axis of the plot in Figure 4.5 shows the cumulative posterior model probabilities. The variables are ranked according to their "importance" in the model from the variable with the highest PIP at the top to the one with the lowest PIP in the bottom of the plot. If the explanatory variable's effect on the dependent variable is negative, the cell is coloured with red colour (lighter in greyscale). If the effect is, on the contrary, positive the cell is blue (darker in greyscale). White colour indicates that the variable is not included in the model.

From the graph it is visible that around 30-40% of all included variables are present in the best models. The signs of the estimated regression parameters are consistent across different models - they are thus robust to the inclusion of other regressors.

Table 4.7: Description and summary statistics of variables

Variable	**Description**	**Mean**	**SD**
Publication year	Year of study's publication	2004.29	5.44
Number of observations	Number of observations (countries) in each study	155.57	399.04
Year of the 1st observation	Year of the first observation in a primary study	1967.21	10.40
Timespan	Timespan of the observations' evolvement in a primary study	27.64	9.17
Effect size	Effect size of inequality on GDP growth	-0.03	0.24
SE	Standard Error of the effect size	0.07	0.16
Publication date	=1 if a study is published before the Lehman Fall	0.75	0.43
Publication type	=1 if a study is a working paper, 0 if journal	0.29	0.46
Cross_section	=1 if the data in a primary study is cross-sectional	0.49	0.50
Pooled	=1 if the data in a primary study is panel	0.51	0.50
Time_series	=1 if the data in a primary study is time-series	0.00	0.06
High-quality Gini	=1 if only high-quality income data is used	0.59	0.49
Low-quality Gini	=1 if only low-quality income data is used	0.07	0.25
High&low-quality Gini	=1 if both high and low-quality income data is used	0.33	0.47
Gini type	=1 if Gini is taken at the beginning of the period, 0 if it is an average of the entire period	0.66	0.47

Table 4.7: Description and summary statistics of variables

Variable	**Description**	**Mean**	**SD**
Gini on income	=1 if Gini is based on income data	0.72	0.45
Gini on expenditure	=1 if Gini is based on expenditure data	0.01	0.12
Gini adjusted	=1 if Gini is an adjusted (usually by DS method) income inequality measure	0.27	0.44
OECD sample	=1 if the size effect is estimated only for OECD countries	0.35	0.48
LDC sample	=1 if the size effect is estimated only for Less Developed Countries	0.13	0.33
OECD&LDC sample	=1 if the size effect is estimated for both OECD and LDC countries	0.52	0.50
Country level	=1 if the analysis in a primary study is at country level	0.77	0.42
Regional level	=1 if the analysis in a primary study is at regional level	0.23	0.42
Other inequalities	=1 if inequalities other than income (human capital, land ownership inequality) are included in primary studies	0.22	0.42
D&S data	=1 if a Deininger and Squire (1996) dataset is used in a primary study	0.35	0.48
Jain data	=1 if a Jain inequality dataset is used in a primary study	0.03	0.18
Lis data	=1 if a Luxembourg Income Study inequality dataset is used in a primary study	0.08	0.27
Wiid data	=1 if a World Institute for Development Economics Research inequality dataset is used	0.19	0.40
Other data	=1 if any other than mentioned above datasets is used in a primary study	0.34	0.47

Table 4.7: Description and summary statistics of variables

Variable	Description	Mean	SD
OLS	=1 if OLS is a used estimation method	0.49	0.50
FE	=1 if Fixed Effects is a used estimation method	0.18	0.39
RE	=1 if Random Effects is a used estimation method	0.04	0.21
GMM	=1 if GMM is a used estimation method	0.20	0.40
Simultaneous	=1 if simultaneous equations (2SLS,3SLS etc.) are a used estimation method	0.05	0.22
Other estimations	=1 if other estimation methods are used	0.02	0.14
Country dummies	=1 if country effects (country dummies, country-based subsamples) are accounted for	0.20	0.40
Education	=1 if an education measure is used as a control variable	0.57	0.49
Institutions	=1 if a measure of institutional quality is used as a control variable	0.09	0.29
GDP per capita	=1 if GDP per capita is used as a control variable	0.93	0.25
Investment	=1 if an investment measure defined as I/GDP is used as a control variable	0.31	0.46
Democracy	=1 if a democracy dummy is used as a control variable	0.10	0.31
X	=1 if a foreign trade measure is used as a control variable	0.15	0.35
Human capital	=1 if a measure of human capital accumulation is used as a control variable	0.19	0.39

Table 4.7: Description and summary statistics of variables

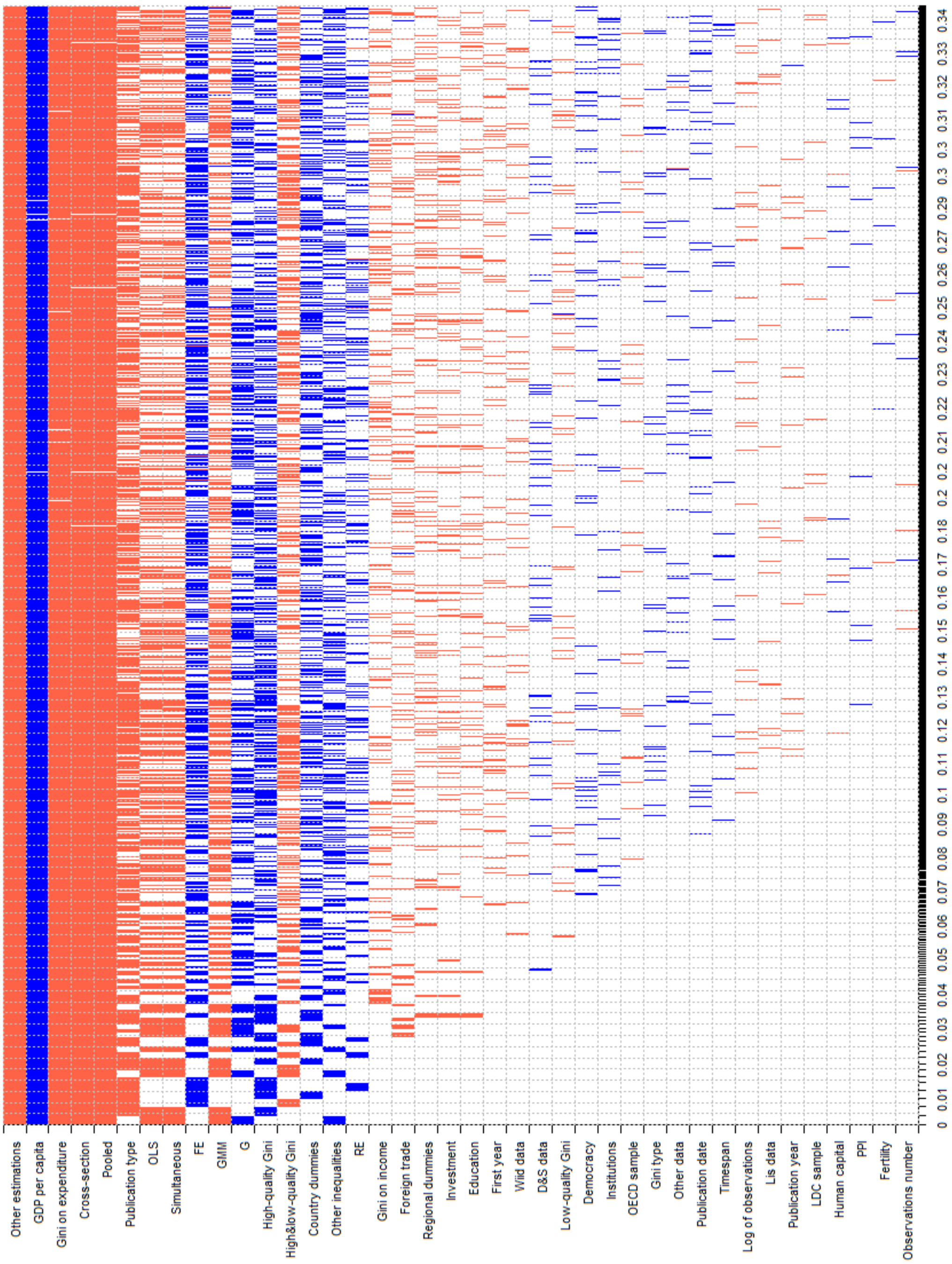
Variable	Description	Mean	SD
G	=1 if government consumption/GDP is used as a control variable	0.20	0.40
Fertility	=1 if a measure of fertility is used as a control variable	0.12	0.32

Table 4.8 presents the numerical outcome of the BMA procedure (first 3 columns). Additional information including posterior densities for important variables (with PIPs higher than 0.5) can be found in Appendix B. The left side of the Table 4.8 shows posterior means (Post Mean), posterior standard deviations (Post SD) and posterior inclusion probabilities (PIPs). Posterior mean and standard deviation can be interpreted as an estimate coefficient and its standard error in a linear regression. The PIP allows to assess, whether a particular variable should be a part of the true model, and can be perceived as the significance parameter - p-value. In order to analyze the significance of regressors we follow the approach of Eicher et al. (2011) and Havranek & Irsova (2015), who state that PIPs exceeding 0.5 provide significant information about the response variable's variation. Variables with PIP values between 0.5 and 0.75 are considered to carry weak significance, PIPs between 0.75 and 0.95 imply substantial significance, between 0.95 and 0.99 - strong significance, and PIPs higher than 0.99 are labeled decisive.

The results in table 4.8 suggest that there exist several variables that significantly influence the variation in our response variable.

Other estimates This variable turns out to be the most crucial one in terms of influence on the effect size value in question. The variable is equal to 1 in case other than OLS, FE, RE, GMM or simultaneous systems estimation methods are used in the primary literature's regressions. To be precise, this category includes time-series analysis, MLE and FGLS (feasible generalized least squares) estimation methods. The category's posterior mean is rather high and negative in magnitude (-0.426) with the PIP equal to 1 (decisive significance). However, such strikingly high values can be explained by the low number of estimates within the category. Only 12 observations out of overall 562 fall into the category of Other estimation methods. This outcome is thus not as reliable as it seems at the first glance.

Figure 4.6: Model inclusion in Bayesian model averaging



Note: Response variable is the inequality on GDP growth effect size estimate. Data is winsorized at 1% on both distribution's sides. Columns depict individual models. Variables are arranged by PIPs in descending order on the vertical axis. Blue color (darker in greyscale) = the variable is included and the estimated sign of its effect is positive. Red color (lighter in greyscale) = the variable is included and the estimated sign of its effect is negative. White color = the variable is not in the model. Cumulative PMPs are presented on the horizontal axis.

Table 4.8: Explaining the differences in the effect size estimates

	Bayesian model averaging			Frequentist check (OLS)		
Response Variable	Post Mean	Post SD	PIP	Coef.	Std. er.	p-value
Other estimations	-0.426	0.099	1.000	-0.488	0.278	0.078
GDP per capita	0.143	0.035	0.997	0.147	0.044	0.001
Gini on expenditure	-0.243	0.068	0.995	-0.241	0.082	0.003
Cross-section	-0.598	0.149	0.992	-0.603	0.288	0.037
Pooled	-0.632	0.156	0.991	-0.668	0.306	0.029
Publication type	-0.037	0.030	0.675	-0.040	0.023	0.080
OLS	-0.073	0.076	0.512	-0.146	0.047	0.002
Simultaneous	-0.087	0.092	0.508	-0.170	0.046	0.000
FE	0.046	0.049	0.506	0.004	0.022	0.856
GMM	-0.048	0.051	0.504	-0.097	0.023	0.000
G	0.033	0.045	0.446	0.050	0.025	0.051
High-quality Gini	0.020	0.027	0.432	0.023	0.033	0.490
High&low-quality Gini	-0.021	0.028	0.419	-0.024	0.036	0.501
Country dummies	0.019	0.027	0.380	0.036	0.017	0.039
Other inequalities	0.016	0.025	0.335	0.030	0.018	0.099
RE	0.016	0.038	0.191			
Gini on income	-0.006	0.017	0.166			
Foreign trade	-0.012	0.033	0.148			
Regional level	-0.007	0.020	0.140			
Investment	-0.005	0.015	0.112			
Education	-0.003	0.010	0.081			
First year	0.000	0.000	0.073			
Wiid data	-0.002	0.009	0.058			
D&S data	0.002	0.008	0.057			
Low-quality Gini	-0.003	0.015	0.053			
Democracy	0.002	0.010	0.049			
Institutions	0.002	0.010	0.045			
OECD sample	-0.001	0.005	0.034			
Gini type	0.001	0.005	0.034			
Other data	0.001	0.007	0.032			
Publication date	0.001	0.006	0.029			
Timespan	0.000	0.000	0.027			
Log of observations	0.000	0.003	0.026			
Lis data	-0.001	0.006	0.020			
Publication year	0.000	0.000	0.019			
Human capital	0.000	0.003	0.015			
LDC sample	0.000	0.004	0.015			
PPI	0.000	0.003	0.014			
Fertility	0.000	0.003	0.010			
Observations number	0.000	0.000	0.010			
Constant	0.755	NA	1.000	0.562	0.133	0.000
Observations	562			562		

GDP per capita The inclusion of the GDP per capita parameter into regression seems to produce on average 0.143 higher effect size coefficients than if not included. This independent variable is the most commonly used one in the regressions of primary studies (523 out of 562 observations). The PIP implies strong significance with the value of 0.997.

Gini on expenditure The posterior mean value suggests the negative impact of Gini based on expenditure on the resulting inequality on GDP growth effect size estimate. Inequality measure (Gini) in primary studies is based whether on income data (pre-tax or post-tax) or on expenditure data. Yet, only Gini based on expenditure is significant in our case and it is much higher in magnitude than Gini based on income.

Cross-section The cross-sectional structure of data seems to produce significantly lower inequality on GDP growth effect size estimates according to our BMA results. The PIP is strongly significant and the posterior mean is equal to -0.598. Compared to another "important" variable **Pooled** (which is also strongly significant), the impact of cross-sectional data structure is slightly lower in magnitude. Both variables' coefficients are though negative. This contradicts the results of De Dominicis *et al.* (2008) ME model, which provides with the evidence of higher values of effect size in case of panel data techniques. Yet, when estimating the regression with hierarchical linear model, the authors obtain an insignificant coefficient of a varible named *Pooled*, suggesting that data structure does not anyhow influence the direction of the inequality/growth relationship.

Publication type Working papers on average tend to produce the effect size estimates, which are about 0.037 smaller than those obtained by journals, supporting De Dominicis *et al.* (2008), who also obtain a negative and significant coefficient estimate for this variable. The authors suggest that the following result could be biased, since the majority of working papers rely on cross-sectional data, which is yielding high negative effect size values. "We may therefore partly be picking up the effect linked to the structure of the data" - write De Dominicis *et al.* (2008). Nevertheless, this is not likely to be our case since pooled data structure (which is highly present in journals' datasets) produces even more negative effect size estimates according to our BMA results.

Estimation methods All estimation methods applied in primary studies, with the PIPs higher than 0.5, turn out to have a "real" effect on the effect size of inequality on economic growth. OLS, Simultaneous systems and GMM seem to carry the effect of the same size and relatively the same magnitude. In particular, studies using these estimation method report more negative estimates of the effect size. The effect size coefficient obtained by the use of the FE, however, is significant and on average about 0.046 points higher than its counterparts. RE estimation is not a significant variable in our BMA model.

Gini The variables indicating the quality of Gini coefficient used in primary studies differ in their signs. The use of high-quality Gini yields positive coefficient, while the use of both high and low quality Gini results into a negative value with almost the same magnitude. If other inequalities apart from income inequality (human capital inequality, land ownership inequality) are included in the regression, the effect size tends to be 0.016 higher. Since the average value of the effect size in our dataset is negative, a positive value of 0.016 means that when the study includes a measure of inequality other than income, the estimate coefficient associated with income inequality becomes smaller.

The inclusion of **Country dummies** in the regression produces more positive effect size value. It becomes on average 0.019 higher. Country dummies mean that country effects are accounted for in the regression, for example country-based sub samples are being used. De Dominicis *et al.* (2008) also conclude that the inclusion of country dummies in the regression produces "effect size estimates that are bigger in absolute value". The authors also find out that the coefficient associated with the inclusion of regional dummies is positive and significant. The conducted BMA exercise, however, doesn't support this conclusion: our regional dummies variable is negative and not significant at all.

Other variables included in the conducted BMA regression have low PIPs, which leads us to believe, that they do not help explain the variability in the inequality on GDP growth effect size estimates. Thus, in order to check the reliability of the BMA results, we conduct the frequentist OLS check as a robustness exercise. Its results are presented in the right-hand side of the Table 4.8. The columns show the coefficient's value, its standard error and a p-value. It is thus analogous to the previous three columns with the BMA results. We perform the frequentist check for only those variables, whose PIPs exceed 0.3, since other variables do not carry information about variation in the response variable.

Most of the obtained results are confirmed by the conducted Frequentist OLS check with the standard errors clustered at study level. All variables have the same coefficient signs in both model specifications and their magnitude is likewise very close in value. The majority of variables with PIPs higher than 0.3 are significant at least on a 10% level. The exception are only 3 variables: FE, high-quality Gini and high&low quality Gini.

Chapter 5

Conclusion

The present thesis focuses on the topic of income inequality and its effect on economic growth. Both theoretical and empirical literature varies in its views on the direction of inequality/growth relationship making it difficult to arrive to unequivocal conclusions. This meta-analysis explores the extent of heterogeneity in the published earlier empirical papers estimating the effect size of inequality on GDP growth. Meta-analysis is a useful way of revealing and explaining contradictive results of empirical literature; it serves to measure the excess between-study variation and reveal the presence of publication bias arising due to the authors' lack of objectivity.

There already exists a meta-analysis on the following topic published by De Dominicis *et al.* (2008). The authors conducted the research on a sample of 37 studies (journals and working papers) published from 1991 to 2008. The principal conclusion of the De Dominicis *et al.* (2008) article is that one can not simply speak of a positive or negative correlation between income inequality and economic growth. Since the authors of primary studies rely on different data samples varying in quality and estimation methods, the magnitude of the estimated inequality/growth effect size coefficient is to a large extent affected. Yet, De Dominicis *et al.* (2008) reveal several interesting patterns emerging in the primary literature. Particularly, (i) least developed countries and longer growth period variables yield more negative and significant inequality on growth effect; (ii) studies applying fixed effects estimation method obtain higher coefficients; (iii) the effect becomes weaker when regional dummies and additional measures of inequality are included as moderator variables in the regression; (iv) the income's definition and the quality of the data substantially affect the results.

This thesis' objective is to update the De Dominicis *et al.* (2008) dataset by newly written studies, published after year 2008. Moreover, the present research applies modern sophisticated meta-analytical estimation techniques in order to reveal the degree of publication bias and explain the heterogeneity in the primary studies' results. The research is based on the dataset of 562 estimates obtained from 58 primary studies (with the majority being journals); 64 % of estimates are negative while the mean of all reported estimates is equal to -0.03.

The meta-analysis is conducted in several steps. To begin with, I examine the presence of publication bias based on graphical evidence. The funnel plot of coefficient estimates shows only slight evidence of the publication bias, mainly it indicates the preference of authors to publish negative coefficient results. Typical funnel plots in economics analyses, however, possess much greater signs of the file drawer problem.

Next, I conduct the funnel asymmetry test on 3 samples of estimates: (i) all estimates; (ii) estimates from studies included in the De Dominicis *et al.* (2008) dataset, published before the crisis of 2008; (iii) estimates collected by me, from papers published after the crisis of 2008. Consequently, the results of the test differ based on a sample. The bias towards preferring negative estimates is confirmed for the papers published before the crisis of 2008. The test on a sample of estimates from papers published after the crisis of 2008 confirms the bias in 2 (FE and RE) out of 4 (FE, RE, OLS, IV) test specifications. Nevertheless, here, compared to the before-crisis sample, the bias is towards positive coefficients. The asymmetry test conducted on a sample of all estimates reveals several interesting facts. Firstly, the test (with the weighting) also confirms the overall presence of bias towards the negative effect. The overall bias is evidently driven by the presence of bias in the earlier published studies (that are prevailing in the dataset) since the studies published after 2008 do not contain the signs of bias according to the weighted specification of the test. Secondly, there is no evidence of the direct effect of inequality on GDP growth - no underlying effect is present since the constants (indicating the true effect) are insignificant for the overall sample.

The information mentioned above confirms the first hypothesis of the present publication bias. The second hypothesis indeed proves to be true. The authors are prone to treat statistically significant results as more favourable and over-estimate the true effect size. In reality, there proves to be no evidence of the income inequality effect on the GDP growth at all. There must be other factors than income inequality, which are more important in explaining economic growth. The third hypothesis is also confirmed: the average reported estimate coefficient is slightly more negative in the sample of papers published after the crisis. Yet, there is a bias towards reporting positive coefficient results in the newly published studies, which is proved by the FAT. This is surprising, since one would expect the authors' pessimistic sentiments prevailing after the crisis induce the preference for publishing the negative effect results.

The BMA analysis is the last meta-analytical tool applied in this thesis. It helps to explain heterogeneity in the primary literature results and reveals several interesting observations. Particularly, studies applying FE estimation method obtain higher effect size estimates. The definition of income and the data on Gini quality highly impact the results. If the income measure is based on expenditures rather than income, the resulting coefficient is highly significant, negative and large in magnitude.

Speaking about the quality of Gini coefficient, the studies which use high-quality Gini do systematically report higher effects. If other measures of inequality (human capital inequality, land ownership inequality) are included in the regression, the effect associated with income inequality indeed becomes smaller. The presence of country dummies induces effect size estimates to be bigger in absolute value. Working papers' authors tend to obtain the effect size estimates, which are smaller than those obtained by journals authors'.

The variables indicating the data structure of primary literature's samples are highly significant with both cross-sectional and pooled data structures producing lower effect size estimates. The variables standing for the sample of countries (OECD, LDC) are insignificant in our BMA regression indicating that the inequality to growth effect doesn't depend on the level of country's development.

This research proves that the effect of inequality on growth is not straightforward and is likely not linear. The results vary across used income inequality measures, estimation methods and data structure and quality. A single pattern for inequality/growth relationship is thus not feasible. This implies several suggestions for further research on the topic. It is more appropriate to explore the income inequality and economic growth relationship on a country or regional level, since the mechanisms of inequality on growth effect transmission are evidently substantially different on a global and on a country level. It also sounds promising to research the issue by differentiating the types of inequality, since they seem to produce different effects. Finally, it would be interesting to investigate the problem by looking separately at published and unpublished primary literature sources since it could shed new light on the publication bias patterns by checking for significant differences in the results.

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Appendix A

Studies included in the dataset

Table A.1: List of primary studies used (Dominicis et al. 2008)

Alesina & Rodrik (1994)	Khoo & Dennis (1999)
Banerjee & Duflo (2003)	Knell (1999)
Barro (2000)	Knowles (2005)
Benjamin et al. (2006)	Larrain & Vergara (1997)
Bleaney & Nishiyama (2004)	Li & Zou (1998)
Castello-Climent (2004)	Litschig (2005)
Castello & Domenech (2002)	Mbababzi et al. (2001)
Clarke (1995)	Odedokun & Round (2004)
de la Croix & Doepke (2003)	Panizza (2002)
Deininger & Olinto (2000)	Partridge (2005)
Deininger & Squire (1998)	Persson & Tabellini (1991)
Figini (1999)	Rehme (2002a)
Forbes (2000)	Rehme (2002b)
Galor & Zang (1997)	Schipper & Hoogeveen (2005)
Gylfason & Zoega (2003a)	Szekely & Hilgert (1999)
Gylfason & Zoega (2003b)	Tanninen (1999)
Iradian (2005)	Voitchovsky (2005)
Keefer & Knack (2002)	Zhu (2001)
Kenworthy (2004)	

Table A.2: List of primary studies used (own search)

Bagchi & Svejnar (2015)	Hsing (2005)
Barro (2008)	Iftikhar & Amanat (2012)
Castello (2007)	Malinen (2013)
Chan et al. (2014)	Ncube et al. (2014)
Cingano (2014)	Shahbaz et al. (2014)
Dabla-Norris et al. (2015)	Szeles (2013)
David & Hopkins (2011)	Thewissen (2014)
Ezcurra (2007)	Townsend & Ueda (2006)
Fawaz et al. (2014)	Woo (2011)
Halter et al. (2014)	Yamamura & Shin (2009)
Hasanov & Izraeli (2011)	

Appendix B

BMA diagnostics & Alternative specifications

Figure B.1: BMA, Prior and Posterior Model Probabilities

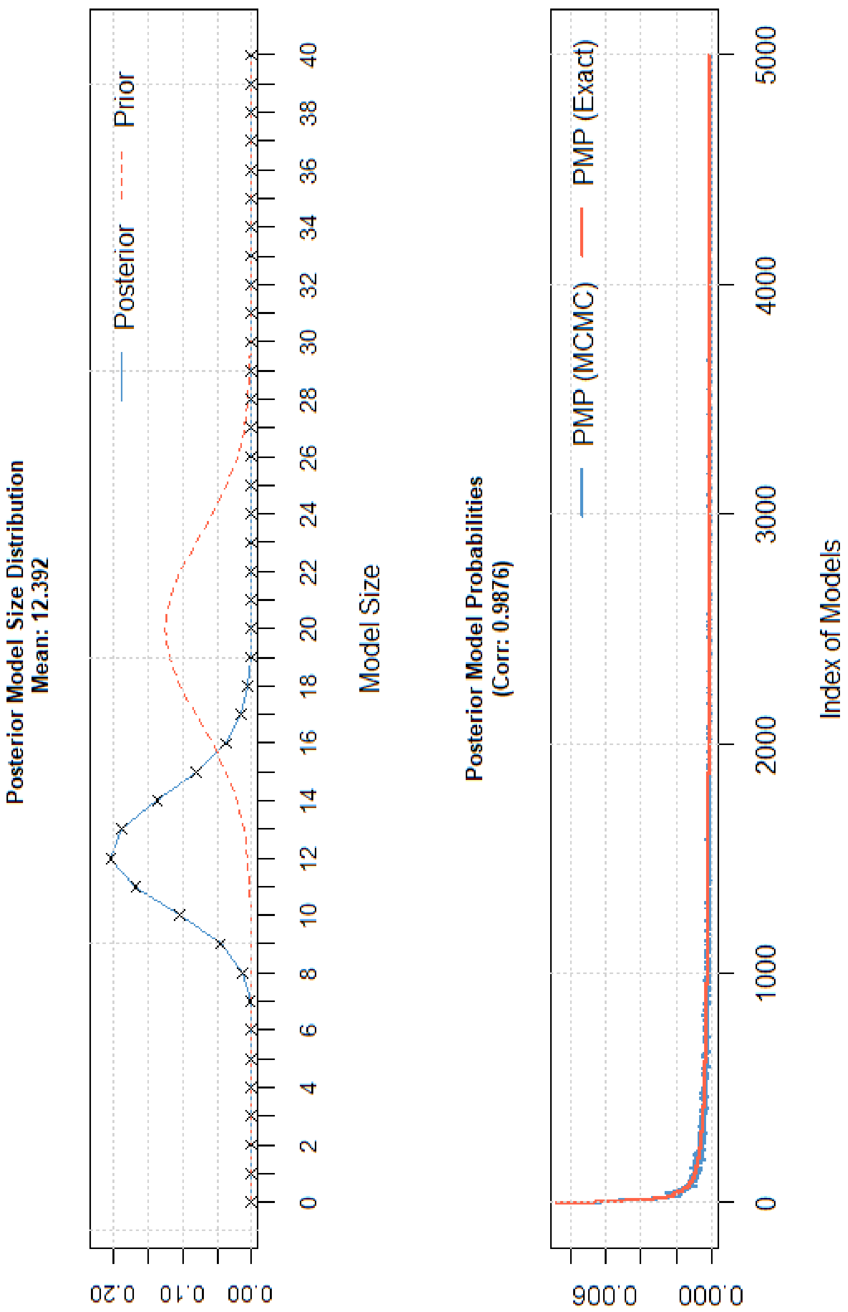
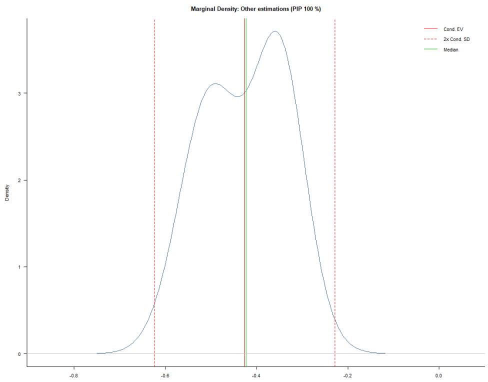
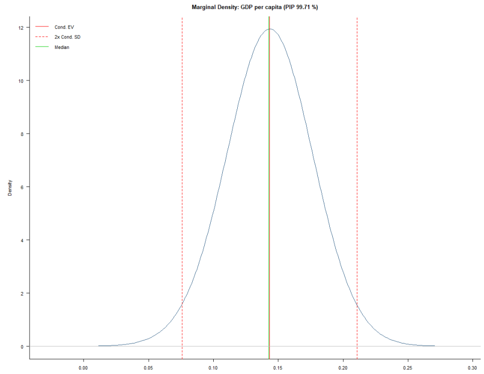


Figure B.2: Posterior Densities for Variables with PIP > 0.5

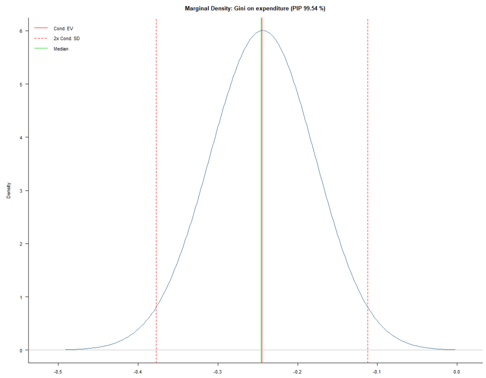
(a)



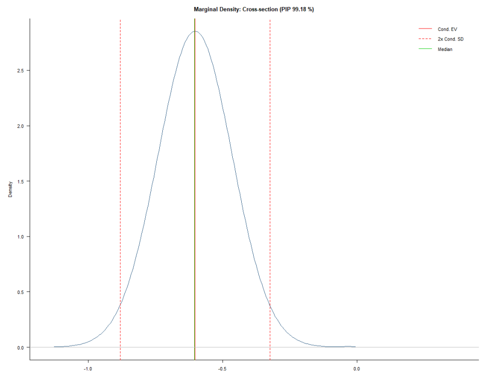
(b)



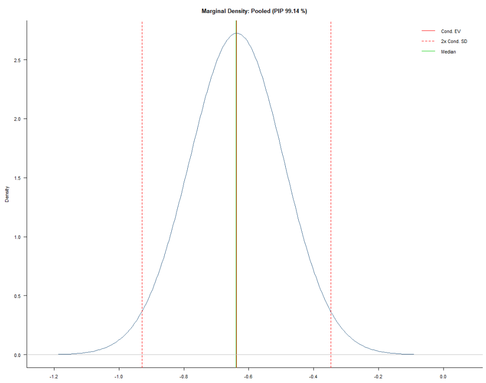
(c)



(d)



(e)



(f)

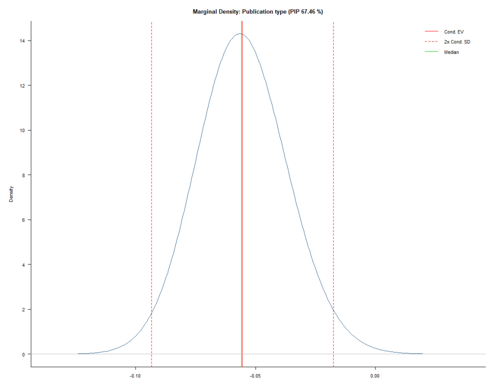


Figure B.3: Posterior Densities for Variables with PIP > 0.5

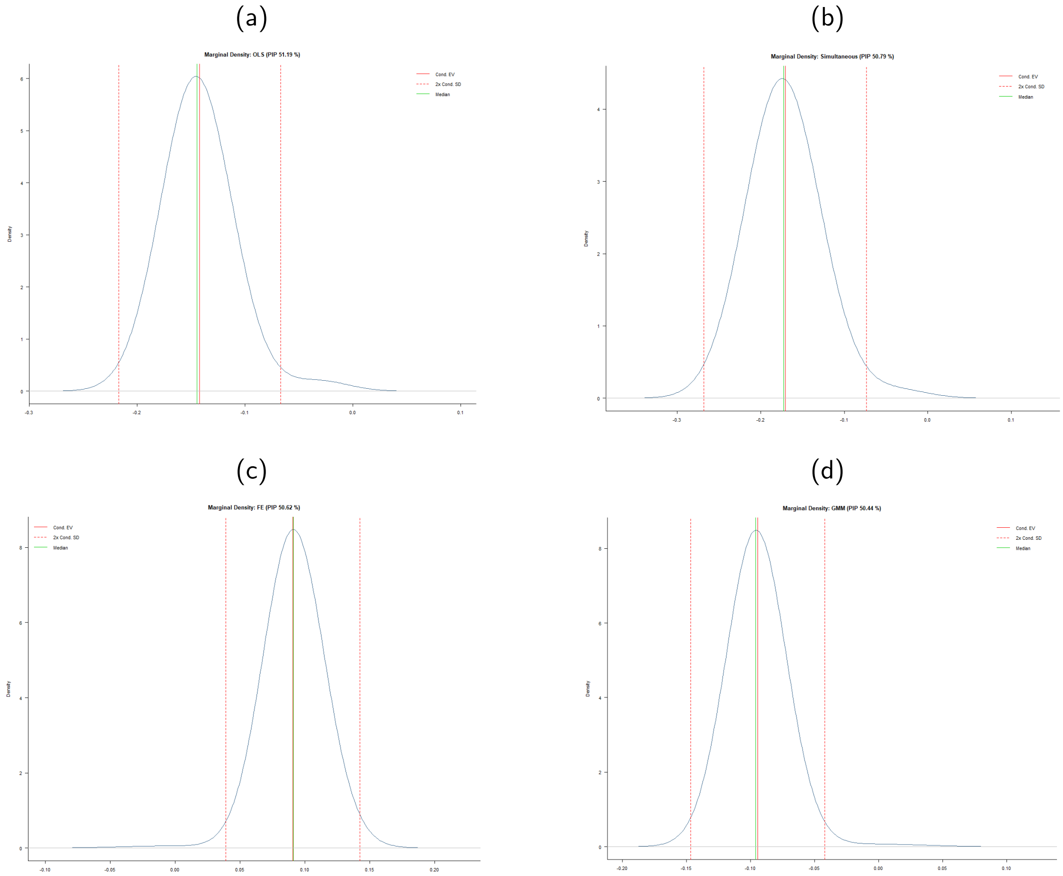


Figure B.4: BMA, $mprior = random$, $g = BRIC$

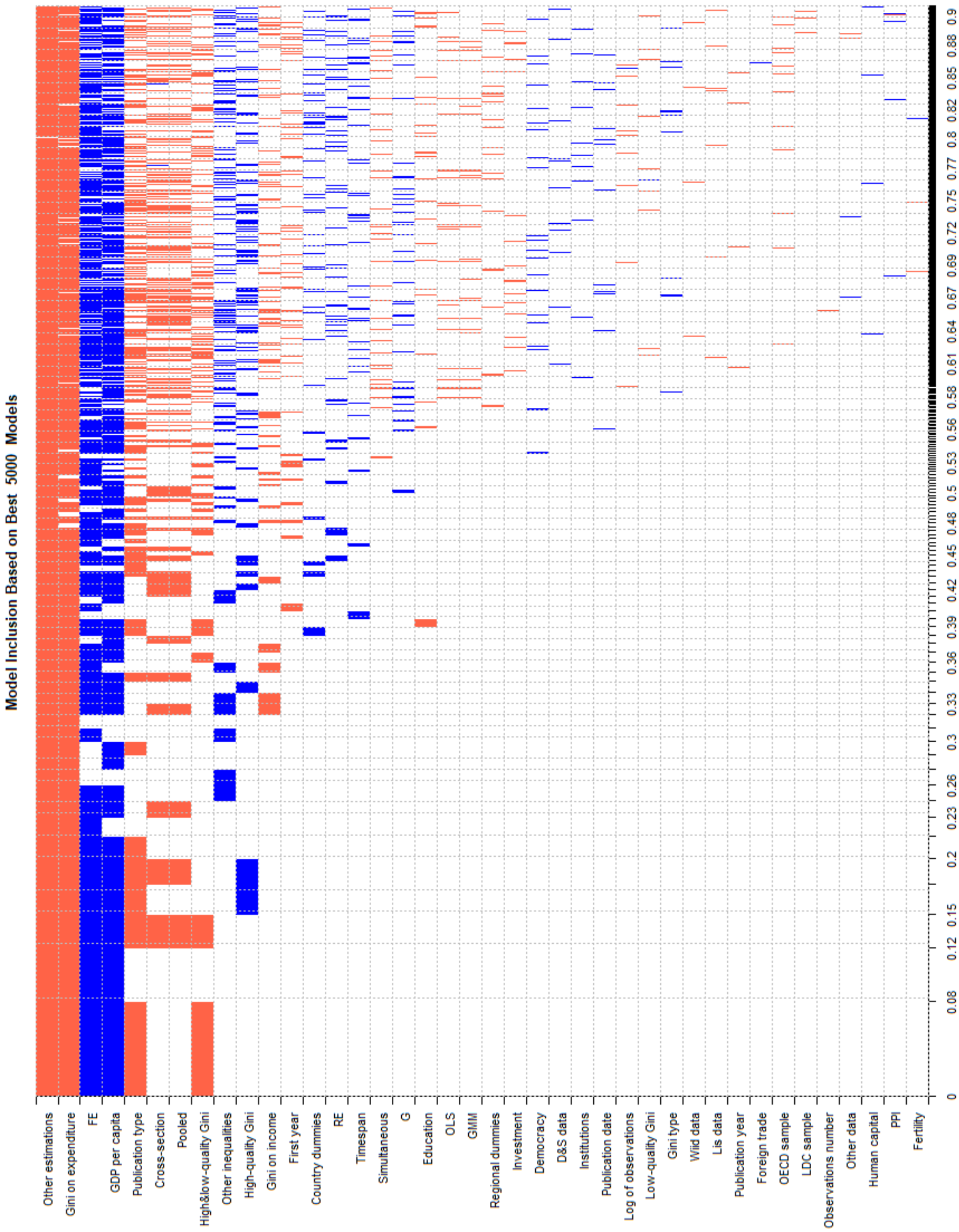


Figure B.5: BMA, $mprior = uniform$, $g = BRIC$

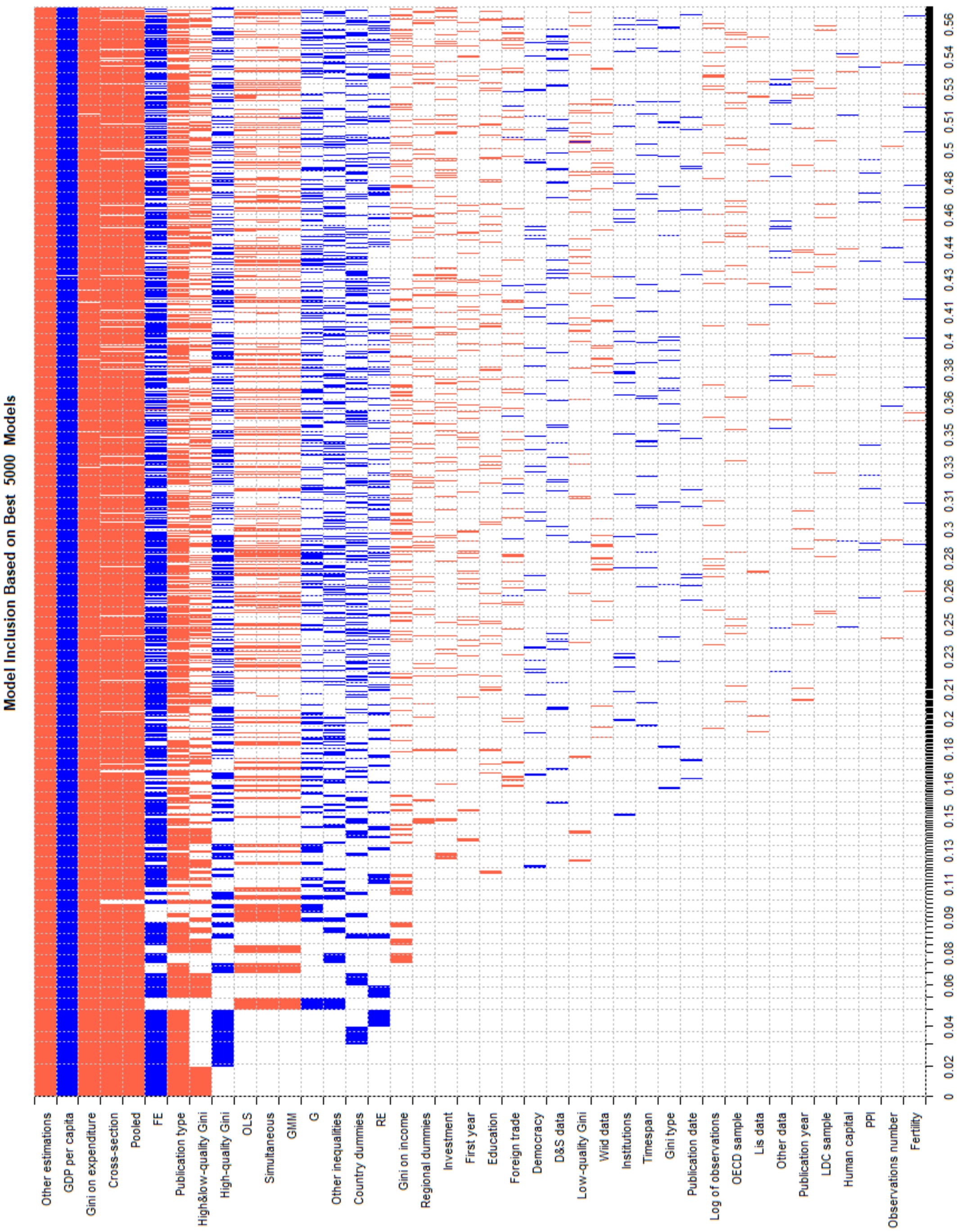
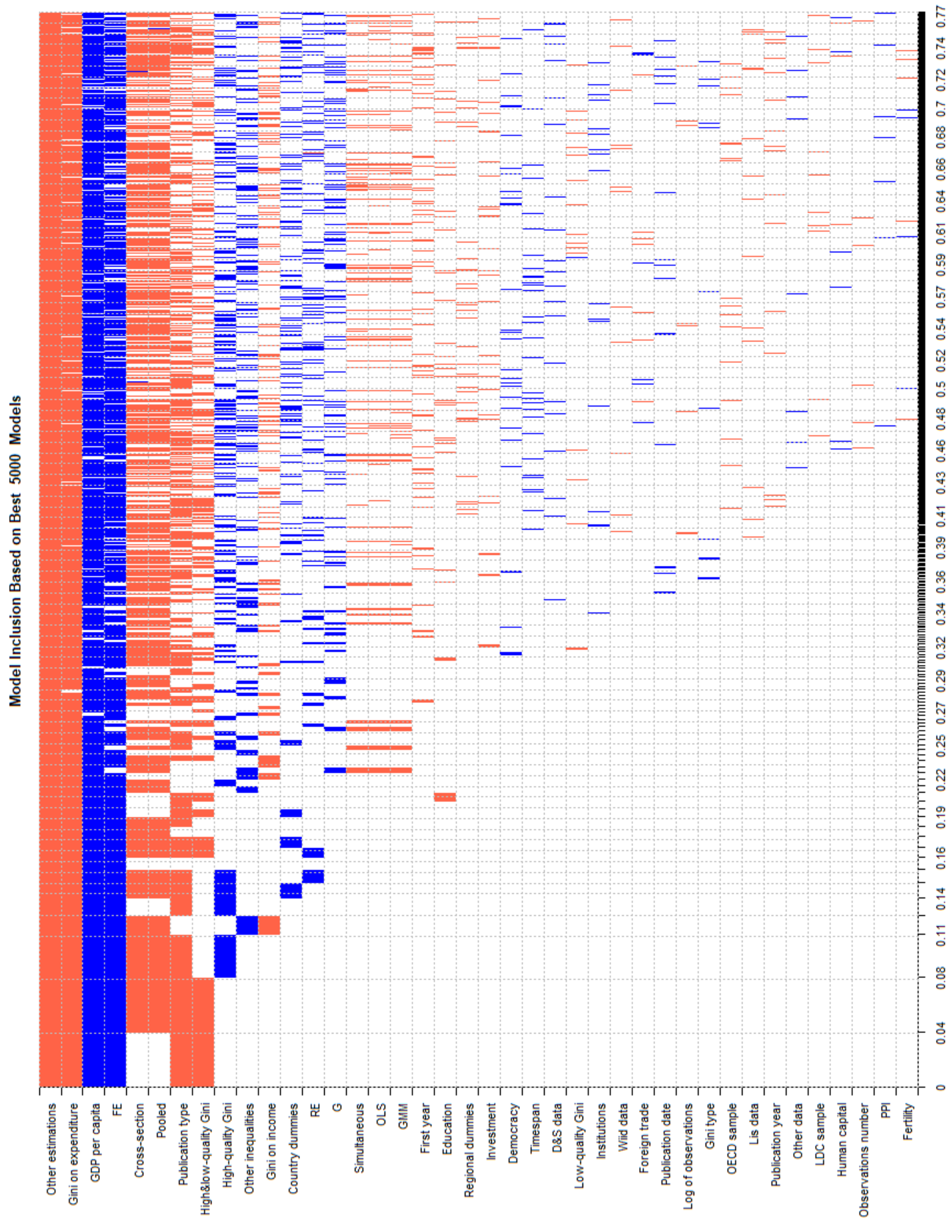


Figure B.6: BMA, $mprior = random$, $g = UIP$



Appendix C

Correlation matrix

Figure C.1: Correlation matrix for explanatory variables included in heterogeneity analysis